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# EFFECTIVENESS OF ENERGY EFFICIENCY INCENTIVE PROGRAMS

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EFFECTIVENESS OF ENERGY EFFICIENCY INCENTIVE PROGRAMS

BY

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ABSTRACT

This work addresses the effectiveness of energy efficiency (EE) incentive programs in reducing electricity consumption and assisting states in meeting their energy policy goals. EE programs provide financial incentives to encourage consumers to make investments in energy efficient equipment and reduce energy consumption. This study carries out a quantitative analysis to provide insights into EE programs performance. In two empirical applications, the research examines program performance on two levels: national coverage including all US-based utilities in the first application and state performance in the second application.

The first empirical application examines stipulated energy savings from electric utilities across all states and compares the outcome to an econometric model that estimates savings from observed consumption. This study examines panel data from the contiguous US spanning eleven years from 2005 to 2015, to estimate the effect of EE program total expenditures on electricity demand. We find that although EE investments have been effective in reducing energy consumption, the modeled magnitude of these energy savings implies that EE programs have had a smaller effect on energy consumption than claimed by electric utilities over the same period.

The results imply a price elasticity of energy efficiency ranging between 0.29 - 0.54; indicating a rebound effect. Consequentially, energy savings are less than proportional to the increase in energy efficiency. However, consumers benefit from an increase in energy services, since they get more of the service, for less cost.

The second empirical application examines the cost-effectiveness of state-specific EE programs. The application employs econometric analysis to mimic an experimental research design using observational data from states with different energy policies in EE investments. This methodology evaluates program performance between states with aggressive EE policies and states with moderate programs. The differential effect of EE program implementation (treatment) in those states is examined in the context of a difference in differences approach and synthetic control method. The study examines the performance of the state with the highest per capita investments in EE: the state of Rhode Island.

We assessed the energy efficiency policy of Rhode Island and compared its outcome to Maine and New Hampshire. Findings suggest that there is not a statistically significant effect on residential consumption, as a result of the substantial increase in EE expenditure, in RI during the period 2008 to 2015. However, a re-evaluation of the Rhode Island EE policy, using the synthetic control method (SCM) identifies that by the year 2015, annual per-consumer residential electricity consumption in Rhode Island was 97 kWh (1.34%) lower, on average, than it would have been in the absence of the increased EE programs.

The research also identifies that energy efficiency improvements have welfare implications on various levels: individual, local, national and international. The outcomes from improvements in energy efficiency are not limited to energy savings but influence a wide range of benefits such as job creation and improved living conditions. Finally, the research provides insights by comparing the levelized costs of energy efficiency and renewable energy. We find that the cost of renewable energy production is now very close to the cost of reducing energy use through energy efficiency programs. Continuing downward trends in the cost of renewable energy technologies such as solar and wind may suggest a change in the priorities of states energy incentive programs in the near future.

However, it is important to note that this comparison only includes the financial cost, and does not consider the full social cost.  For example, this comparison does not consider other social costs, such as aesthetic effects of large-scale solar energy facilities, or wildlife impacts of wind turbines.

ACKNOWLEDGMENTS

This dissertation has helped me refine my knowledge of the research process. Thankfully, it has been a good learning experience. However, this research would not have been possible without the support of my wife, Julietta, and my advisor Dr. Jim Opaluch. Julietta has given me support and assistance every day for many years. Julietta inspires me to try harder, to improve myself. I am eternally grateful for all the things she has done to support me through this process. My advisor, Dr. Opaluch, has been invaluable in guiding me through the graduate program. His view of the bigger picture and his vast experience have made my work better. I am indebted to him.

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# Chapter 1. Introduction

The heated debate on climate change has led to an increase in environmental research and the creation of more environmental policies. In recent years, there has been a growing interest in the literature on energy efficiency (EE). The objective of this research is to evaluate the effectiveness of EE programs, specifically those that provide financial incentives to reduce electric energy consumption. The discussion is no longer solely centered on the scarcity of natural resources for traditional energy production. The drive for energy efficiency programs and sustainable economic development has been an energy policy goal in the US, since President Carter's administration. However, technological innovations, which were expected to overcome obstacles to future growth and economic progress, have not been able to keep up with the ever-increasing demand for energy. The increase in energy consumption, driven primarily by population growth and increased global wealth, is correlated with rising average atmospheric temperatures. This has become the center of one of today's most complex problems. Environmental economists today are facing the challenge of using economic theory not only as a tool to explain and understand the utilization of natural resources but as a means to shape a new relationship between the economy and the environment.

As early as 1975, Wally Broecker, in the Journal of Science, forewarned: "Are we on the brink of a pronounced global warming?" (Broecker, 1975). Four decades later, the correlation between carbon emissions and the dangers of global temperature rise, has increased the international concerns. For example, the UN decided to take action in the form of a global climate conference. Specifically, at the 2015 United Nations Climate

Change Conference in Paris, nations agreed to a drastic reduction in greenhouse gas emissions in order to limit global temperature increase. The global climate governance signatories to the UN Framework Convention on Climate Change acknowledged the problem and demanded action. Their actions were driven by good intentions translated into a new set of universal goals, the Sustainable Development Goals (SDGs) promoting energy efficiency and renewable energy programs. However, efficiency and renewable energy programs require the implementation of energy policies, and their effectiveness is a subject of controversial debate. Criticism includes the selection bias issue that reduces the effectiveness of the programs. At the same time, an increase in energy consumption as a result of the implementation of the programs leads to overestimates of the energy savings. This topic is examined analytically and described in the research as the rebound effect.

The target proposed by the climate summit in Paris introduced policies to hold “the increase in the global average temperature to well below 2 degrees Celsius above pre-industrial levels" (COP21, 2015). An adjustment of this magnitude requires the immediate reduction of carbon output. That would translate into immediate and drastic technological adjustments via a binding and universal agreement by all nations of the world on specific climate-related policies. In practice, the only two available options to achieve such an outcome would be a decrease in the overall demand for energy or the increase in the supply of clean energy, free of greenhouse gas emissions. Governments around the world have adopted both solutions in varying analogies in the hope of curbing carbon emissions. The first option, a decrease in energy consumption via practices and technologies that allow us to maintain the same level of service, is referred in the bibliography as energy efficiency (EE). A typical example of an EE program is the offer of rebates by utilities to consumers to encourage investments in new EE technologies and equipment. EE incentive policies have a broad scope and consist of specific programs like those that target electricity consumption, natural gas and deliverable fuels (oil, propane). This research focuses on electricity incentive programs. Currently, policymakers and stakeholders focus on adopting incentive programs to increase investments in EE. They are hoping that the actual effect of EE programs in reducing electricity consumption will indeed have a positive effect in reducing greenhouse gas emissions. The relationship between funds spent on EE investments and corresponding electricity savings is critical because we are unable to make the necessary technological improvements in the short-term. For the examined period, 2005-2015, state policymakers have increasingly encouraged utilities to invest public funds in financial incentives for EE. The annual expense for the year 2015 was more than double the annual expenditure five years earlier. This trend seems to continue unimpeded; therefore, questions about the duration and effectiveness of the programs ought to be examined. In 2015, the total spending for energy efficiency from electricity utility incentive programs was $5.7 billion (Table 7: Annual Costs of Electricity Efficiency Program Implementation) (EIA, 2015).

The relationship between actual funds spent in the form of incentives on EE investments, and the corresponding electricity savings, has not been fully researched and documented. Policymakers adopt energy efficiency incentive programs because they are thought to be effective. They are driven by energy policy stemming from public opinion and the scientific data on global warming. The idea is that the marginal cost of increasing energy efficiency is less than the marginal cost of producing additional energy. Acceptance of the concept that EE programs are essential drivers for cost-effective energy conservation has created a framework where subsidies for EE have been viewed as an appropriate key strategy. For that reason, states compete to achieve energy savings by increasing their spending for EE programs each year. This is an analogical reasoning understanding of the EE impact on energy consumption. According to this reasoning, similarities between two systems are presumed to support the conclusion that some further similarity exists. Adopting this reasoning, stakeholders presume that by increasing spending on EE programs, there will be an analogous decrease in the demand for energy. This reasoning by analogy approach is dominant in the energy market. Programs, policies, and expectations, in general, are driven by assumptions that are based on this concept. This research explores the reasoning by analogy approach and compares program outcomes using the economic principles angle.

Therefore, the goal of this study is to examine and evaluate the effectiveness of the above-mentioned electricity EE programs that provide financial incentives for reducing overall energy consumption in the contiguous US for a period of eleven years examining data on 3,745 utilities. The quantitative task is difficult and tedious because of the size of the dataset examined. However, the importance of the study justifies the challenge. A better understanding of the mechanism of financial incentives will help state energy policy-makers to be more effective. The focus is on the economics, and not the driving politics, to identify precisely how subsidies and EE programs result in reducing energy demand, specifically in the case of electricity consumption. It is also essential to develop a comparative understanding of the energy policies related to renewable energy (RE) generation. As the cost of RE decreases and the cost of EE progresses, there is a tipping point where the two technologies will be competitive. It is also important to understand the temporal cost of EE and if there are economies of scales in the implementation. The contemporary analysis, introduced in this research, provides better insights on how public funds must be spent to optimize results. Governments and market leaders can utilize available economic tools to significantly increase the effectiveness of technological developments in the fields of renewable energy (RE) generation and energy efficiency (EE) technologies. The target is to reduce the amount of greenhouse gases emitted into the atmosphere, and both EE and RE can contribute significantly towards this goal. The new energy equilibrium will be a result of simultaneous changes in technological innovations in RE production and behavioral changes using EE. Understanding the relationship between financial incentive programs and energy investments will uncover a path for sustainable development.

The energy savings that are the product of EE programs are reported by utilities and the magnitude of the savings reported essentially defines the unit cost. To achieve additional savings, the trend has been to increase subsidies continually. A better understanding of the practical results of the mechanism of subsidies will assist governments in adopting appropriate policies that would balance the negative externalities of fossil fuels with sustainable economic growth and prosperity via the better use of new technologies and methodologies. Economic theory identifies reasons that the savings from utilities are lower than utilities expect and report. This research identifies and describes the barriers that reduce the expected savings and increase the cost of EE. The empirical application quantifies this discrepancy and examines different EE policies.

There are known barriers when evaluating the cost-effectiveness of EE programs for electricity. This is because a substantial amount of errors may occur, due to inconsistencies across utility companies, specifically on how they measure energy savings and adjust estimates for free riders or spillover effects. Additionally, electricity energy savings based on engineering models typically don’t capture changes in consumer behavior, and as a result, tend to overstate energy savings due to not considering the rebound effect. Any evaluation, therefore, should take under account free riders and the rebound effect both of which increase the cost of EE.

This study examines the reported electricity savings from utilities and compares their magnitude to econometric models of electricity demand. The objective is to understand if the obstacles identified from literature result in different than expected outcomes in energy savings. The expectations of EE programs are enormous. Based on the annual reports that administrators of energy efficiency programs submit to the Energy Information Administration (EIA), savings from electricity efficiency programs from 2005 to 2015 have reduced total electricity sales across the nation by about 1%. Investments in energy efficiency do contribute to the solution to climate change by steering the energy market in the right direction. This paper, however, assesses if the magnitude of the effectiveness of investments in energy efficiency meets the reported quantities. Understanding the effectiveness of EE programs will help shape future decisions.

In the literature review, we summarize the role of the energy efficiency programs since they were first introduced and describe the economic theory underlined in the research. In the methodology chapter, there is an analysis of the quantitative econometric methods involved to evaluate the effectiveness of the EE programs. The Research Findings chapter provides estimates of the cost-effectiveness of EE programs and examines the hypothesis that energy efficiency programs are a predictor of energy consumption. Additionally, a comparative analysis examines EE programs with a different magnitude in programmatic costs to evaluate effectiveness. In the Conclusion, there is a discussion related to the EE incentive programs and policy implications. Finally, the Figures and Tables chapter presents quantitative supporting material for the research.

## Chapter 2. Literature review

This study examines the effectiveness of energy efficiency subsidy programs specifically for the electricity market. The following literature review examines this and reviews the related conceptual framework. The concepts of energy efficiency in general and energy efficiency for the electricity market, are reviewed chronologically as they first emerged along with the correlating scientific and socioeconomic events that drove relevant public policy. It is also depicted that despite the high amounts of funding dedicated on these subsidies, the published data on the effectiveness of energy subsidy programs using observational data rather than reported data is scarce hence documenting the importance of this study. In addition, it is exhibited that in the published research there is no explicit universal model that allows governments to calculate, compare and contrast savings accrued as a direct result of efficiency programs. In the cases where so-called undisputable savings are claimed, the true drivers of those gains for different end uses are also not clear. For example, some of the published or expected gains from these energy efficiency programs do not take under consideration the rebound effect or take-back effect; a well-established phenomenon in economics that paradoxically reduces gains due to behavioral or other systemic responses. These responses, in published past cases of expected gains from the adoption of new technologies, have limited or even completely offset the expected benefits.

Historically, EE programs appear to have been put in place because of a combination of scientific data and public opinion pressures regarding environmental concerns. These concerns have primarily been focused on the idea that greenhouse gas emissions and their environmental impacts could reach a tipping point that would present a clear and present danger to global economic growth and prosperity. Over a span of four decades, researchers, experts, and theorists came to the realization that climate change is a severe threat, so great, it must be addressed jointly by the international community.

The literature review chapter is partitioned into two sections; the historical background and the theoretical framework. The historical background reviews literature that follows depicts, compares, contrasts, and analyzes the following: how EE programs came to be in the first place; the energy gap; regulation policies; and the paradox of energy efficiency improvements and how their effectiveness has been determined in the published bibliography. The theoretical framework introduces concepts, in economic principles, as to why improvements in efficiency may differ from expected energy conservation results.

## 2.1 Historical Background

### 2.1.1 Energy efficiency programs defined

According to the American Council for an Energy-Efficient Economy (ACEEE), energy efficiency (EE) programs target a reduction in energy demand by offering financial incentives for investments in new, clean and more efficient equipment and technologies. EE programs have always offered subsidies to consumers to upgrade appliances, heating and cooling equipment, building envelopes. They have also aimed at long-term behavioral change, through education. The ultimate objective is to reduce energy consumption, which in turn reduces dependency on the fossil fuels that produce greenhouse gas emissions and lead to climate change. It is only during the past few years that EE programs have been developed as stand-alone programs. Initially, EE programs were part of the demand side management programs (DSM) which are designed to encourage consumers to modify their pattern and level of electricity consumption. The historical evolution of these programs sheds light on their importance and the contextual socioeconomic circumstances under which they were conceived and implemented in the first place.

### 2.1.2 Energy efficiency and conservation

It is necessary to highlight the distinction between EE and energy conservation and to define more analytically the term efficiency. Energy conservation is generally defined as a reduction in the total amount of energy consumed. Energy conservation may or may not be achieved with the implementation of EE investments. This distinction is critical in understanding issues such as the "rebound and backfire effect", described in this chapter, whereby the demand for energy may increase in response to EE investments, because of a decrease in the cost of energy supply. Also, energy conservation implies a behavioral change to save energy that doesn't necessarily includes investments in equipment. Then again, EE is a synonym to improvements in equipment and technology that use energy. Efficiency in energy is typically defined as the energy services provided per unit of energy input. In lighting applications, for example, efficiency is the ratio of luminous flux to power, measured in lumens per watt. As the index of efficiency increases (ratio of units of service to energy units) it is implied that per unit of input, we have better service, an improvement in illumination. As a result, investments in EE technologies will produce the same or better service for the same amount of energy input.

### 2.1.3 Specification for energy efficiency programs

The industry assesses the effectiveness of EE programs by using engineer-derived stipulated estimates. For example, in the case where someone purchases an LED fixture, it is estimated that there will be savings of 30 kWh per year for a period of 15 years. This example describes the situation where a consumer will purchase and replace an incandescent light bulb of 60 watts with an LED of 10 watts and will operate it for 600 hours annually. The replacement will generate savings of 50 watt-hours for every hour of operation or 30 kWh annually.

In order to increase the market penetration of the new efficient lighting technology, the EE program will subsidize the price of the LED to lower the purchase price and increase the number of efficient light bulbs sold. The same mechanism applies to many types of heating and cooling equipment, electronic devices, water heaters, home appliances and building materials.

The process just described has a clear rational but may suffer from a number of assumptions that produce unrealistic expectations. Selection bias is the principal economic concern related to subsidies (Hartman, 1988). Selection bias arises from the fact that treated individuals differ from the non-treated for a reason or reasons other than treatment status. In the case of EE programs, there is a concern that the group of consumers that make EE investments is not representative of the general public. In other words, subsidies - the treatment to increase EE investments - may benefit higher income populations instead of benefiting everyone (Herring, 2006).

In addition to selection bias, the spillover effect could potentially increase the effect of an EE program. Spillover refers to energy savings produced by decisions beyond those directly associated with participating in an EE program. Conceptually, spillover can be achieved by both participants and non-participants (Violette & Rathbun, 2014). Participant spillover occurs when consumers choose to implement additional EE investments after having participated in an EE program. Non-participation spillover occurs when energy savings are realized by consumers that implement EE measures without having participated in a particular EE program.

### 2.1.4 Brief history of energy efficiency programs

The idea of a viable perpetually growing economy has always been appealing to many. Although, the consequences of exponential growth, when resources are finite, has been clearly expressed in cornerstone works like 'The Limits to Growth', a report for the Club of Rome's Project on the Predicament of Mankind (Meadows, Meadows, Randers, & Behrens, 1972). In the book, the authors proclaimed in the early 70s "if the present growth trends continue unchanged, the limits of growth on this planet will be reached sometime within the next hundred years." (p. 23). This seminal work which dealt with factors that limited human economic and population growth predicted that the economy would probably collapse some time before the end of 20th century. At the time it was published, such predictions were criticized as dystopic science fiction. Clearly, the belief in a perpetually growing economy and the need for clean energy, energy efficiency, and sustainability had not yet entered the mainstream as an essential field of study in the early 70's. A drastic change appeared in the mid 70's when the concepts of energy efficiency and demand response programs appeared heavily in the literature. In the bibliography, they are referred to by the term Demand Side Management (DSM) programs. They were developed following the October 1973 oil embargo by the members of the Organization of Arab Petroleum Exporting Countries (Gellings, 1985). The crisis that followed that embargo, combined with the following 1973–74 stock market crash, was considered the most devastating event on the U.S. economy since the Great Depression (Perron, 1988). Public opinion at the time was a significant determinant for policy change aimed at energy conservation and strategic fuel independence. Typically, DSM programs were subsidized with a small percentage of total revenue from customers, around 2-3% in successful implementations and sometimes received funding from the state or federal government (Geller, 2004).

According to the U.S. Energy Information Administration, DSM programs consisted of the "planning, implementing, and monitoring activities of electric utilities which are designed to encourage consumers to modify their level and pattern of electricity usage." The EIA issued reports on them up to the year 2000, and the primary objective of most DSM programs was to provide cost-effective solutions in the energy market. DSM programs promoted behavioral changes that helped defer the need for new sources of power, including generating facilities, and transmission and distribution capacity additions. They had focused on decreasing energy consumption and shifting demand to off-peak times, such as nighttime and weekends. In any case, environmental goals were not the objective for these forms of energy-efficiency programs that were first introduced in the 1970s.

### 2.1.5 Utilities and regulation policy

Utilities have a long history of operation. Thomas Edison opened the first public electricity company in early 1882. A steam-powered electricity generation station at Holborn Viaduct in London supplied the local consumers with electric light. Edison used the method of direct current (DC) to supply electricity. The DC method is constrained in its range of service, and power stations had to be within a mile of the consumers. Later the same year, in September 1882 in New York, Thomas Edison opened the Pearl Street Power Station (Hargadon & Douglas, 2001).

Utilities for many decades operated as monopolies. When the New York Stock Exchange crashed in 1929, the US entered the Great Depression, and many electric companies across the nation collapsed. In 1935, Congress passed the Public Utilities Holding Company Act (PUHCA) to prevent unfair practices in the energy sector. PUHCA was the government's first attempt to regulate the energy industry. The regulation limited utilities' operations to a single state and thus made them subject to effective state regulation. Before the introduction of the regulation, in 1932, the eight largest utilities controlled 73% of the investor-owned electricity market (Hyman, 1988).

Following the 1973 energy crisis, Congress passed the Public Utility Regulatory Policy Act (PURPA) in 1978, with the expectation that this bill would reduce US dependency on foreign fossil fuels. This legislation was part of the National Energy Act, designed to promote energy conservation and increase investments in renewable-energy supplies by establishing a program for small hydroelectric power projects (Pub.L.95-617, 1978). The policy was designed to diversify the US power supply and encourage energy conservation. This would be accomplished via regulations that required utilities to purchase power from new producers when their own supply was low. It was the administration of President Carter that started to emphasize the importance of energy investments for sustainable development. Making energy policy a top priority, he signed PURPA in an effort to remedy the energy crisis. PURPA restructured the energy market and encouraged energy efficiency and hydropower investments. President Carter associated the energy crisis in one of his speeches with the "moral equivalent of war" (Bennet, 2006) and pointed out that energy efficiency was the "quickest, cheapest, most practical source of energy" (Bennett, 2006 p.462). According to President Carter's philosophy on energy issues, government involvement must promote energy policies in the way that David Freeman (Freeman, 1974) and Amory Lovins (Lovins, 1976) advocate. Both David Freeman and Amory Lovins indicated that America's energy needs could be more easily met by investing in technologies and equipment that use less energy to perform the same tasks as less efficient appliances and methods. Since the days of the Carter administration, all the following US presidents have supported energy policies that target both the demand and supply aspects of the energy market. Energy programs continued to encourage behavior change in energy demand, such as using less energy and shifting consumption to off-peak periods like nighttime and weekends (Darby, 2006). Following the second oil crisis of 1979, which drove demand for more fuel-efficient automobiles, more and more economists were studying energy consumption and behavior to a great extent to determine overall efficiency and savings. Stemming from independent research, and based on the well-known phenomenon known as the Jevons Paradox, economists Leonard Brookes and Daniel Khazzoom (Saunders, 1992) concluded that increased energy efficiency paradoxically tends to lead to increased energy consumption. They conducted their research on the fuel efficiency that was achieved for automobiles on average, while overall consumption had continued to increase.

### 2.1.6 The energy efficiency gap

The idea of an energy efficiency gap and the market barriers to energy efficiency investments was part of the literature in the 70s. Literature, including the IEA, identifies the difference between observed and optimal investments in EE, as the energy efficiency gap.

The concept of energy efficiency as a policy strategy was developed by Lovins who supported investments that will use less energy to produce greater economic output (Lovins, 1976). Later this decade, it was suggested that when selecting durable goods, consumers trade off capital cost and energy cost as if they heavily discount future energy savings (Hausman, 1979) (Train, 1988). The failure of consumers to make energy-saving investments that have a positive net present value is the core concept explored by economic literature according to the EE gap. The same consumer behavior is observed in the vehicle market where consumers undervalue future fuel savings (Allcott & Wozny, 2014) (Helfand & Wolverton, 2009). These studies suggest that the way consumers make decisions about energy efficiency investments leads to lower spending on energy-efficient products that would be expected if consumers made all positive net present value investments. This behavior has come to be known as the energy efficiency gap. However, the energy efficiency gap concept has been met with skepticism. The use of analyses showing investments in energy-saving technologies that appear profitable from a net present value perspective has caused even more skepticism (Soest & Bulte, 2001). Many economists question the regularity of the decision-making models, and the cost assumptions stated to identify the existence of underinvestment in energy efficiency. Some researchers have stated that the energy efficiency gap has been used as political justification for intervention in energy efficiency markets through efficiency tax credits and other subsidies and claim that empirical evidence for a significant energy efficiency gap is limited (Allcott & Greenstone, 2012). On the other hand, the literature in energy economics has long identified that market failures can lead to low levels of investments in energy efficiency. Lack of information, environmental externalities, and principle-agent issues can drive EE investment to suboptimal levels (Gillingham & Palmer, 2014). Recently, economists explain the energy efficiency gap as a result of systematic behavioral biases in consumer behavior (Allcott, Mullainathan, & Taubinsky, 2014).

### 2.1.7 Sustainable development

As stated, a gradual progression in the research from energy independence to topics like environmental awareness and later to that of climate change have become increasingly relevant to the topic of energy efficiency and renewable energy. There have been discussions that go as far as 200 hundred years ago regarding the impact of civilization on the environment since the time of demographer, political economist and country pastor Thomas Robert Malthus (Rogers, Jalal, & Boyd, 2012). However, it was not until the mid-70s that that applied examples of this conceptual progression became a practice with programs like property tax incentives for the purchase of residential solar technology. These incentives programs involved two states in 1974, twenty-eight states in 1976 and increased to forty-four states by 1981 (Hinds, 1981). The same period, we have the introduction of DSM programs offered by electric utilities. DSM programs started modestly in the 1970s as a response to the increasing concerns about dependence on foreign fossil fuels. The programmatic cost increased rapidly during the late 1980s with the introduction of incentive programs for utilities to pursue least-cost or integrated resource planning principles (Eto, 1996). In 1987, the notion of sustainable development emerged in the literature in the modern sense with the publication of the Brundtland report by the UN World Commission on Environmental and Development (Keeble, 1988). Scientists began to research and understand that environmental concerns like stratospheric ozone depletion, loss of biodiversity and acid rain were international and required a transboundary response. On the other hand, there was a disincentive to any change because utilities' gross income was stemmed by the throughput incentive: a contribution to gross income that occurred with every energy unit due to the fact that the unit variable price recovered some of a utility’s fixed costs (Morgan, 2013). In the mid-80s it became apparent that a government regulated separation of a utility’s revenues from its unit sales and profit volumes was necessary; a sort of "decoupling." Electric utility DSM programs peaked in 1993, spending $2.7 billion or about one percent of U.S. utility revenues.

### 2.1.8 Decoupling

A regulatory tool that effectively disassociated the utility's profits from its sales of the energy commodity became known as "decoupling." It is the mechanism that disrupts the alignment of the rate of return with meeting revenue targets and encourages firms to nudge consumers toward reducing energy use and adopting energy efficiency programs themselves. This indifference to sales and focus on energy efficiency changed the overall utility environment forever. Since then, the utility's revenue from fixed costs has remained at levels regulators determine to be fair and reasonable while the financial risk for the utility decreases. Decoupling has been recognized as a win-win strategy to both utility companies and the environment by actively encouraging energy efficiency because it ensures that a utility still recovers short-run fixed costs if consumption declines as a result of carbon reduction policies (Shirley, Lazar, & Weston, 2008).

### 2.1.9 Climate change and energy efficiency

In the early 1990s, the literature began to broaden its attention to include global environmental issues such as global warming and climate change (Bergh, 2016).

However, it is only after the change of the millennium that US EE programs increased the incentives for electricity and natural gas investments significantly.

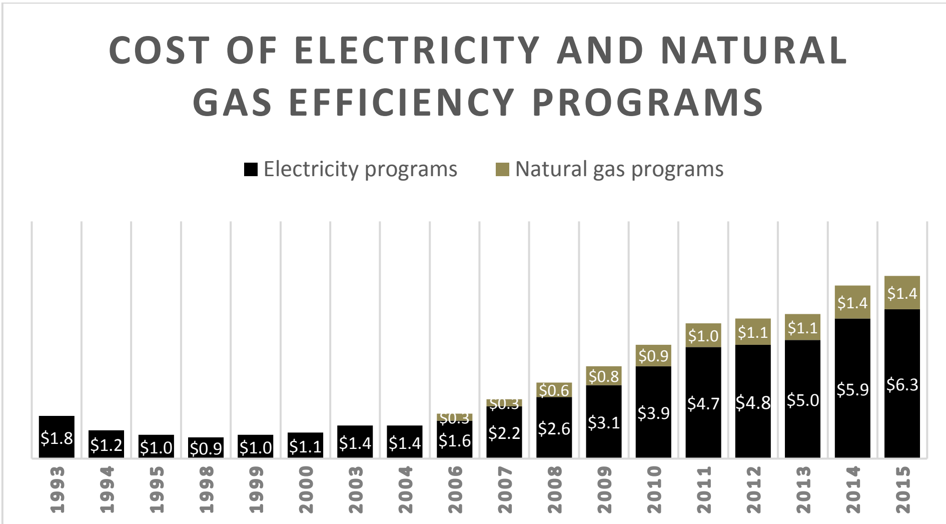



Figure 1: Electricity and natural gas efficiency programs ($ million)

*Note*. Data for electricity and natural gas efficiency programs in the United States from the American Council for an Energy-Efficient Economy: State scorecard 2016

2.1.10 Deregulation policies

Deregulation means that the generation process in the electricity market will be open to competition; however, the transmission and distribution of the electricity market will remain a regulated monopoly. The market openness in electricity generation provides customers a choice of how they purchase and use electricity.

Deregulation policies play a crucial role when examining the ownership status of electric utilities because they signify whether the utilities are directly regulated by the government, which affects the administration of energy-efficiency programs (Blumstein, Goldman, & Barbose, 2005). The Federal Energy Regulatory Commission (FERC) introduced Orders 888, 889, and 2000, which allowed all power producers fair access to transmission lines for safe and reliable power (Sioshansi, 2001). These regulations essentially broke up integrated utilities by forcing them either to sell their power plants to a third party or, transfer them to an unregulated affiliate. To address concerns about reliability and safety of the shared power grid, regulators decided to empower two groups: the regional transmission organizations (RTOs) and the independent system operators (ISOs). This legacy instituted by FERC is in place today, and the two groups monitor and control the operation of the power grid across most regions of the US (Tomain, 2002).

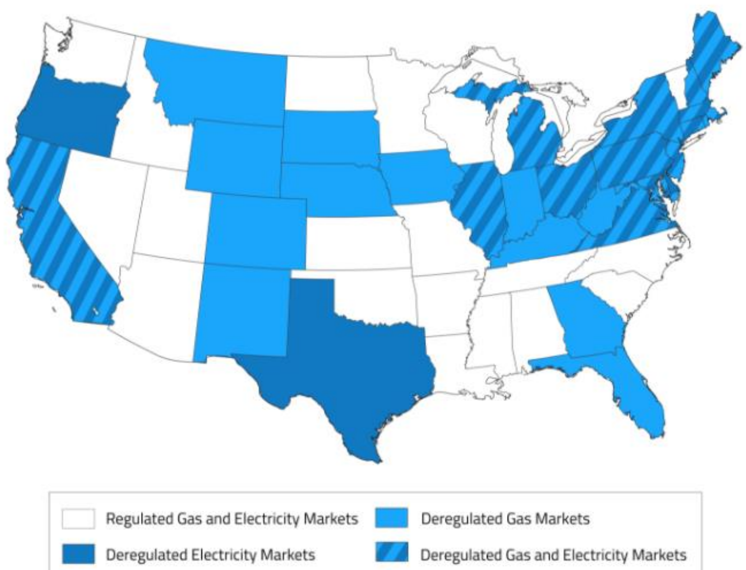



Figure 2: Deregulated energy - States and markets

*Note*: Map was reprinted from an Eisenbach Consulting LLC article in the ElectricChoice.com website

### 2.1.11 Energy efficiency programs and global temperature

Publications of the findings on greenhouse gas emissions and the ever-rising average global temperature fueled public concerns regarding greenhouse emissions. In 2003, British prime minister Tony Blair and Swedish prime minister Göran Persson sent a joint letter to the European Commission (Ruda, 2003). They urged that if a government's fundamental goal is to promote economic growth and prosperity, it had to be combined with the reduction of greenhouse gas emissions with a "decoupling" of economic growth from its environmental impacts. In his speech on sustainable development, Mr. Blair said, "It is clear that Kyoto is not radical enough." Once again, the concept of energy efficiency was employed and was being called to accomplish increasingly diverse goals. At 2015, United Nations Climate Change Conference in Paris, policymakers otherwise reluctant to implement climate policies fueled by renewed public interest legislated the reduction of energy demand by investing in clean, more efficient, non-greenhouse gas emitting equipment and technologies. For a second-time governments were driven by external factors: global warming statistics and public outcry. The pledge to drastically reduce greenhouse gas emissions via behavioral change through education alone is by definition a long-term goal. In contrast, the tool immediately available to governments to achieve the 2015 Climate Change Conference goals was the adoption of specific energy efficiency (EE) programs propagated by subsidies as part of a new comprehensive climate policy framework. As a result, during the past few years, EE programs have developed as stand-alone programs separate from the demand response (DR) programs. As program budgets increased, EE and DR programs were developed in parallel but followed distinct paths. In EE programs' development, electricity utilities often play the role of the administrators with state governments mostly playing the role of regulator. They are perceived as successful programs with a twofold gain: offering both environmental and economic benefits. Many states have broadly adopted the current objectives of EE programs, and in 2015, State-supported System Benefit Charges (SBC) used to generate funds for electric EE programs via a per kWh charge on electric bills reached 1% of total electricity revenues. Of course, there is a wide range in SBC collections with the states of Rhode Island, Massachusetts, and Vermont leading the nation with EE program spending equating to more than 6% of their state's electricity revenues. Concerning monetary burden, in Rhode Island for example, in 2015, the annual cost per residential household associated with EE's System Benefit Charge (SBC) was $73. At the same time, other states have more moderate programs and many states that don't support energy efficiency programs at all.

### 2.1.12 The role of incentives in energy efficiency programs

Policymakers have identified energy efficiency as a means of combating the rising costs of energy, energy shortages, and climate change. Thus, incentives to encourage energy efficiency were established. Investing in programs for energy efficiency may help accelerate the adoption of innovative technologies and encourage investments in energy efficiency. Consequently, EE programs can lead to a reduction in the growth of energy consumption. The timing of energy efficiency implementation is critical. Financial incentives can contribute to consumers investing in energy efficiency earlier than they otherwise would have (Gillingham, Rapson, & Wagner, 2015).

A theoretical model of a private energy efficiency investment is illustrated in Figure 3:. Given the initial marginal cost MC, the optimum quantity of investment in EE is $Q_1$. Offering financial incentives on EE decreases the marginal cost of the investment. The new optimum quantity is $Q_2$. At this level of EE investments, individuals that would have invested at the initial unsubsidized level $Q_1$will benefit from the incentives (free riders).

Energy efficiency programs are about efficiency change; getting people to adapt existing technologies, such as LED lights, that use less electricity. EE investments can be implemented at any time, and financial incentives may accelerate implementation. We can reasonably expect all consumers to replace inefficient technologies, eventually. The consumers with investments in EE=$Q_2$ should be thought of as the consumers induced to invest in more efficient technologies due to offered financial incentives at time t, who otherwise would have invested in energy efficiency at some future time (t+n). The objective of accelerating the deployment of energy efficiency can be achieved with a number of different programs and policies. As mentioned above, the focus of this proposed research is to assess the effectiveness of financial incentive programs for energy efficiency. In addition to these programs, states support other initiatives such as building energy code enhancements and compliance, transportation policies, appliances and equipment standards, and State government "lead by example programs" as conventional methods of reducing energy consumption. However, utility incentive programs remain the flagship of this effort.

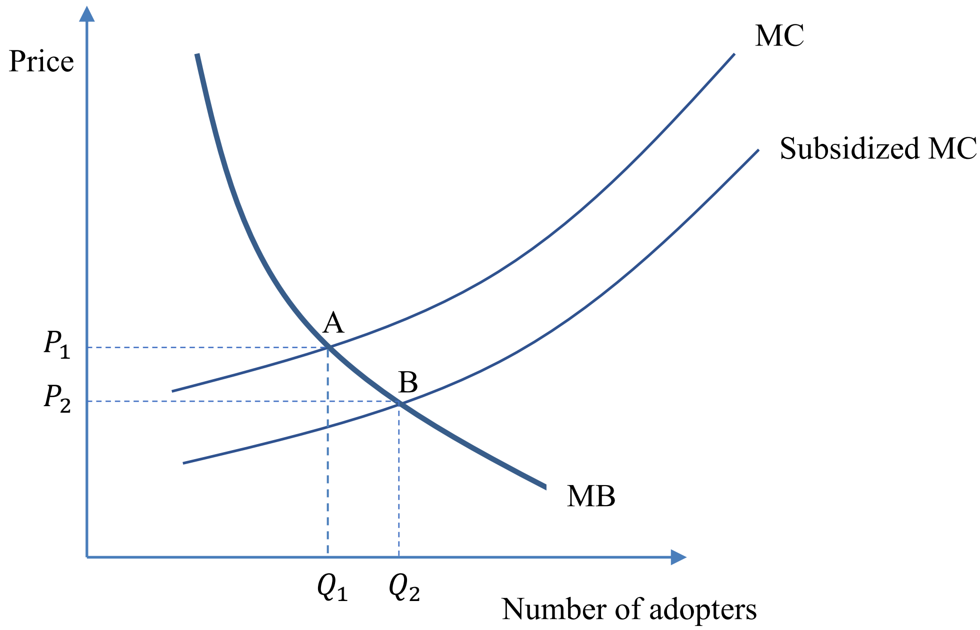



Figure 3: Subsidized marginal cost and free riding

*Note*. The figure demonstrates an increase in EE investments when the marginal cost decreases with subsidies. Given the initial marginal cost, the optimal level of investments in EE is $\boldsymbol{Q_1}$. In the case that an energy efficiency program offers financial incentives and the marginal cost of this investment decreases, the new optimal is $\boldsymbol{Q_2}$. The level $\boldsymbol{Q_1}$ of investments in EE would have been implemented even without the provided financial incentives (free riding).

### 2.1.13 Energy efficiency programs for the electricity market

EE programs are developed in both the electricity and natural gas markets. This thesis narrows the investigation of EE programs to the electricity market, but some perspective is necessary. Electricity programs and natural gas programs are distinct due to different targets and budgets. Electric EE programs have been implemented for decades while natural gas programs only just gained a notable presence after 2006 (Figure 1: **Electricity and natural gas efficiency programs ($ million)**. Regarding the magnitude of their budgets, electric EE programs are much larger with about five times the budgets of natural gas programs. The electric EE programs across the nation target all aspects of economic activity from the residential sector to commercial, industrial and transportation. The electric EE programs are sophisticated and target appliances, lighting and HVAC systems by offering solutions that will decrease consumption while providing the same or better level of service. It is worth mention that during the last few years the US has experienced a revolution in EE lighting solutions with the introduction of light-emitting diode (LED) technologies in all lighting applications (indoors and outdoors). Lighting accounts for about 7% of the total US electricity consumption (EIA, 2016) and LED technology has the potential to reduce this consumption by more than 30%.

### 2.1.14 Energy efficiency programs and effectiveness

In theory, efficiency is measured by the quantity of output divided by the quantity of energy input. Traditionally efficient technologies have had a higher upfront cost, but the promise was that eventually money and energy would be saved. The utilities also faced the challenge of mounting investment costs of new generation environmentally friendly but high-cost power plants just to meet the ever-rising demand. They too had an interest, therefore, in energy efficiency as a resource to decrease capital investments while meeting electricity demand (Geller, 2004). Concerning the cost-effectiveness of EE electricity programs, there is controversy found within the literature. Estimates of the cost-effectiveness of EE programs range from \$0.01 to \$0.22 per kWh saved. Gillingham et al. (2004) estimate the cost of incentive programs at \$0.039 per kWh. Friedrich et al. (2009) used utility and state evaluations for 14 states to estimate an average cost to utilities of \$0.025 per kWh saved. Loughran and Kulick (2004) examined panel data on 324 utilities, between 1989 and 1999, and reported an average cost of \$0.06 - \$0.22 per kWh. Auffhammer, Blumstein, and Fowlie (2008) examined the same period and estimated the cost of energy savings \$0.01 - \$0.08 per kWh. Arimura et al. (2012) evaluated ratepayer-funded DSM expenditures between 1992 and 2006 and estimated expected average cost to utilities of roughly \$0.05 per kWh.

### 2.1.15 Rebound effect and energy efficiency programs

Researchers have questioned the assumption that consumers require the same level of energy services before and after an efficiency investment. The discussion of evaluation of EE programs has focused on concepts that distort program effectiveness and are associated with an increased demand of electricity over time when the cost for the commodity drops with the implementation of EE. This effect is well documented in the growing literature as the "rebound effect" and results in decreased energy savings after EE improvements are implemented. Empirical estimates of the effect were documented in many studies. A paper focused entirely on residential energy savings in countries that are members of the organization for economic co-operation and development (OECD) estimated the direct rebound effect at 30% (Sorrell, Dimitropoulos, & Sommerville, 2009). Empirical evidence from Austria identify the rebound effect for space heating between 20-30% (Haas & Biermayr, 2000).  The estimated rebound effect can differ widely depending on the application (lighting, appliances, building envelop, HVAC), the place and the time of the study. Even more substantial rebound effects that reached 80% were found in the US residential sector over the period from 1995 to 2011. This indicates that policymakers should be aware that the expected energy savings from efficiency improvements may not be achieved (Orea, Llorca, & Filippini, 2015).

### 2.1.16 Evaluation, measurement and verification (EM&V) of EE programs

The practice to evaluate, measure and verify energy-efficiency programs goes back to 1970s and early 1980s and was conducted by federal entities like the US Department of Energy's Weatherization Assistance Program and by State Energy Programs (Vine, Hall, Keating, Kushler, & Prahl, 2010).  EM&V is the collection of methods and processes to assess the energy savings expected from the implementation of energy efficiency measures. The goal is to identify and achieved results with greater certainty and accuracy so that future programs can be more effective. Practically, EM&V process quantifies the benefits of EE as a cost-effective, reliable resource.

Based on the experience in the US, the most important and transferable technical issues are "net savings" (incrementality), evaluation of market transformation programs, and evaluation of the carbon impacts of energy-efficiency programs. Of these, the most significant technical issue is the evaluation of net energy savings (versus gross energy savings). According to a background paper for subsidies in the energy sector, the European Union does not use a consistent evaluation method for EE programs for each member country (Bacon, Ley, & Kojima, 2010). The picture is similar in US and EM&V is evolving along with the of EE programs. Some states provide leadership with their regulatory framework. California and Massachusetts are identified as the principal states in the EM&V framework (Nowak, Molina, & Kushler, 2017).

According to a study prepared by the ACEEE (Nowak, Molina, & Kushler, 2017), the three topics with essential developments in the EM&V process are the: technical reference manuals (TRM), the common practice baselines (CPBs), and the advanced metering-based M&V. The TRM is a classification of EE measures that outlines the expected energy savings either through deemed savings values or engineering algorithms. The CPBs are energy consumption estimates of what a typical end-user would have done and are used as the basis for baseline energy usage. Lastly, advanced metering describes the measurement and verification methodology that use available energy data and incorporate data analytics to improve effectiveness.

## 2.2 Theoretical Framework

Investments in Energy Efficiency (EE) address energy challenges by reducing energy demand. The core idea is that such investments are cost-effective. Furthermore, EE is often treated as a source of energy supply because it can displace electricity generation. For that reason, EE supporters compare the EE marginal cost of saving energy to the marginal cost of producing energy and argue that the energy savings from customer EE programs are typically achieved at a lower cost than the cost of new generation of energy (Yang & Yu, 2015). Additionally, energy generation almost always involves environmental impacts, even in the case of wind and solar generation. Reducing demand can also reduce the need to transmission capacity and reduce peak demand. For this reason, in the literature, EE is described as "first fuel."

Acceptance of the concept that EE programs are essential drivers for cost-effective energy conservation has created a framework where subsidies for EE have been viewed as a critical strategy. For that reason, states compete to achieve energy savings by increasing their spending for EE programs each year. This is an "analogical reasoning" understanding of the EE impact on energy consumption. Stakeholders believe that by increasing spending on EE programs, there will be an analogous decrease in demand for energy. This "reasoning by analogy" approach is dominant in the energy market. Programs, policies, and expectations, in general, are driven by assumptions that are based on this concept.

This research provides a rigorous economic analysis based on economic principles to examine the potential role of efficiency in meeting energy demand. The chapter introduces the economic theory to understand consumer behavior regarding energy use and energy efficiency better. Analytically, the theory explores the rebound effect from principles in consumer theory and derives the welfare implications of the rebound effect. As already mentioned, in the distinction between EE and energy conservation, energy conservation may or may not be achieved with the implementation of EE investments. This distinction is critical in understanding issues such as the "rebound and backfire effect," described in this chapter, whereby the demand for energy may actually increase in response to EE investments, as a result of a decrease in the cost of energy supply.

### 2.2.1 Microeconomic theory - Electricity demand

This section provides a theoretical framework to explain, in economic principles, why improvements in efficiency may have different than expected energy conservation results. The core idea is that the benefits to a consumer (or a producer) of energy services due to the implementation of an EE investment would essentially come down to a price reduction in energy. According to microeconomic theory, this price reduction will drive two effects: an own-price effect and indirect effects of income changes. The first-order effect will most probably reduce the energy savings. The reduced cost of energy services will increase disposable income. Economic agents with improved purchasing power will then increase their expenditure on other commodities, including appliances or services that require energy consumption. The first-order effect of this expenditure would likely increase the quantity demanded energy services, and partially offset energy savings.

In other words, initially, an increase in energy efficiency will reduce the cost of energy services. The law of demand suggests that this will likely increase the demand for energy services. An example of this is an increase in fuel efficiency in automobiles which reduces the cost per mile of driving, leading to an increase in miles driven.

Second, this reduction in the price of energy services leads to an effective increase in disposable income. If energy services are a normal good, this will also increase the quantity demanded

The Slutsky equation (below) demonstrates that the change in the demand for a service that is an outcome of a price change, is the result of two effects; a substitution effect and an income effect.

$$\frac{\partial x_i(p,w)}{\partial \rho_j} = \frac{\partial h_i(p,u)}{\partial \rho_j} - \frac{\partial x_i(p,w)}{\partial w}\ x_j(p,w)$$

Where $h_i(p,u)$ is the Hicksian demand and $x_i(p,w)$ is the Marshallian demand, at price levels *p,* income level $w$, and fixed utility level $u$. The right side of the equation is equal to the change in demand for a service $i$, as a result of a price $p$ change, holding utility fixed at *u;* minus the quantity of service *j* demanded, multiplied by the change in demand for service *i*, when income *w* changes.

Hicksian demand $h_i(p,u)$ is consumer's demand for a bundle of goods and services that minimizes the expenditure at a fixed level of utility *u*. Marshallian demand $x_i(p,w)$ shows the relationship between the price of a service and the quantity demanded. The analysis that follows rests on neo-classic economic assumptions. Economic agents have rational preferences between outcomes, consumers maximize utility and producers maximize profits and all agents act independently on the basis of full and relevant information.

### 2.2.2 The consumer of energy services

Economic theory is based on the assumption that a household, or any entity acting as a consumer, will maximize utility subject to an income constraint. Consumer's preferences can be implicitly described by a utility function $u(x,s_1,s_2)$, where energy services are denoted $s_i$ and non-energy commodities as *x*. In the utility function, we consider two energy services, $s_1$ *and* $s_2$ where $s_2$ encompasses all energy services besides $s_1$. A simplified form of the model would have a one-to-one relationship between energy services and fuels, such that each fuel is used for a single service and each service can be obtained from a single fuel. In addition to this assumption, there would not be any changes in income from investments in efficiency. However, Borenstein (2015) shows in his analysis that as EE investments decrease disposable income, the magnitude of the rebound effect is reduced.

The consumer's model is derived where energy services $s_i$ are provided through the consumption of fuels *j=1, 2* at the price $p_j$. Efficiency ($\eta_{ij}$) is used to produce energy service $s_i$ that is obtained by fuel *j* at the fuel cost of $p_j$ with the corresponding fuel consumption of $f_{ij}$. The consumer has disposable income *w*. Numeraire good *x* has its price normalized to unity. The consumer's problem therefore is given by:

$$\max_{x,s_1,s_2} u(x, s_1, s_2)$$

$$\begin{aligned} \text{subject to } s_1 = &\quad \eta_{11} f_{11} \\ s_2 = &\quad \eta_{22} f_{22} \\ w = &\quad x + p_1 f_{11} + p_2 f_{22} \end{aligned}$$

The solution to the utility maximization problem yields the demand for energy services, denoted $s_i^*$ $(\eta_{11}, \eta_{22}, p_1, p_2, w)$. The demand for energy that maximizes consumer's utility can conveniently be rewritten as $s_i^*$ $(\pi_1, \pi_2, w)$, where $\pi_i = \frac{p_i}{\eta_{ii}}$ is the implicit price of the service $s_i^*$. The corresponding fuel consumption of $f_{ii}^*(\pi, w) = s_i^*$ $(\pi, w)$ / $\eta_{ii}$ .

As energy efficiency for service i=1 changes, with an improvement of $\eta_{11}$, the comparative statics obtained, show how changes in energy services and fuel demand impact (decreased) the implicit price of energy services. With an increase in efficiency, we get the following comparative statics:

$$\frac{\partial s_1^*}{\partial \eta_{11}} = -\frac{p_1 \partial s_1^*}{(\eta_{11})^2 \partial \pi_1} \qquad (1)$$

$$\frac{\partial f_{11}^*}{\partial \eta_{11}} = -\frac{1}{(\eta_{11})^2}\left(s_1^* + \frac{p_1 \partial s_1^*}{\eta_{11} \partial \pi_1}\right) \qquad (2)$$

$$\frac{\partial s_2^*}{\partial \eta_{11}} = \eta_2 \frac{\partial f_{22}^*}{\partial \eta_{11}} = -\frac{p_1 \partial s_2^*}{(\eta_{11})^2 \partial \pi_1} \qquad (3)$$

2.2.3 Direct rebound effect

Following the previous notation, an increase in energy efficiency, $\eta_{11}$, would affect fuel consumption $f_{11}$ from additional use of energy services, due to the decrease in the price of usage $\pi_1$. The direct effect is typically defined in terms of elasticities. Elasticity of demand for *a* with respect *to b* ($\varepsilon_{a,b}$) describes the direct rebound effect as $\varepsilon_{f_{11},\eta_{11}}+ 1$ or equivalently, $\varepsilon_{s_1,\eta_{11}}$.

Energy prices influence consumer's decisions regarding the consumption of energy. As energy prices change, the elasticity of demand for energy would result in different consumer behaviors. If the elasticity of demand for the service is zero, $\varepsilon_{s_1,\eta_{11}} = 0,$ the direct rebound effect would be zero. Equivalently, if the elasticity of demand for the service is -1, $\varepsilon_{f_{11},\eta_{11}}$= - 1, the entire increase in energy efficiency will be realized as a decrease in fuel consumption. The consumer purchases no more of the service when its price falls, and the naïve view of energy saving prevails. For example, doubling gas mileage means consumer uses half as much gasoline.

In contrast, if $\varepsilon_{s_1,\eta_{11}}$ = 1, then we expect a 100% direct rebound effect. The consumer has $\varepsilon_{f_{11},\eta_{11}}$= 0, and there is not any fuel saving from efficiency improvements. The consumer uses exactly the same amount of energy, but gets more service. The price per mile decreases by 50%, but the consumer now drives twice as many miles. There is no reduction in energy use, but the consumer benefits by getting more service. In the case of a greater than 100% rebound effect, i.e., the elasticity is greater than 1, then the 'backfire effect' occurs. More energy is used when energy efficiency increases.

If elasticity falls between zero and -1, the consumer purchases more of the service, but the net effect is less energy is used, and the consumer gets more of the service. For example, if efficiency doubles gas mileage, the price per mile is 50% of what it was. At the lower price, the consumer might drive 50% more miles than previously, while using 25% less gasoline.

Gillingham et al. (2009) provide a summary of previous studies of the estimates of energy own-price elasticities in both the short and long run. It is clear that the influence of energy own-price elasticities in the short run is lower in absolute value than in the long run. Dahl (1993) provides estimates for short-run residential electricity own-price elasticity ranging between 0.14 and 0.44. Bernstein & Griffin (2005), and Hsing (1994) provide long-run estimates for price elasticity related to residential electricity in the 0.32-1.89 range. Those values describe a situation where consumers, in the short run, may increase energy consumption as the cost of energy drops and as cost reduction maintains - in the long run - further increase consumption.

### 2.2.4 Indirect rebound effect

The indirect rebound effect occurs when there is an increase in energy consumption from the consumption of other energy services when efficiency $\eta_{11}$ improves. The indirect rebound effect is due to the income and substitution effect on all the other energy services $s_2$. It can be defined as the direct rebound effect, in terms of elasticities, as $\varepsilon_{f_{22},\eta_{11}}$ or equivalently, $\varepsilon_{s_2,\eta_{11}}$. Energy services $s_2$ will increase with an increase in efficiency $\eta_{11}$ if $s_2$ is a complement service for $s_1$. Respectively, energy service $s_2$ will decrease with an increase in efficiency $\eta_{11}$ if energy service $s_2$ is a substitute service for $s_1$. The indirect rebound effect is challenging to estimate and has received considerably less attention in the empirical literature.

### 2.2.5 Total rebound effect

Let's assume that the utility function is modeled only by the quantity of energy service, *s*, and non-energy service, *x*. A consumer would allocate disposable income between *x* and $s$ in order to maximize utility. The associated utility maximization problem is $\max_{x,s} u(x, s)$. An indifference curve would represent all bundles of (*x,s*) that yield the same utility. In the consumer's utility maximization model, the rebound effect is an outcome of the following process. As technological innovation improves efficiency, the relative cost of the service provided decreases. For example, efficient lighting decreases the cost of operation. Illumination would be consumed in lower per unit price. As a result, a consumer chooses a new optimal bundle, consistent to the new relative prices.

The change in the price of energy services has two effects on the demand of service. The service becomes cheaper relative to other goods which leads to a substitution effect. Secondly, the disposable income increases leading to an income effect. The magnitude of the rebound effect is related to the price elasticity of the service. Consumer disposes the available income in two commodities or services, $x$ and $s$, conditional on the initial prices of $x_A$ *and* $s_A$. The consumer maximizes utility $U_A$ at given prices and income constraints, as described in

**Figure 4: Consumer's total rebound effect**.

Let's assume that $s_B$ represents energy services of an equipment that has improved and become more energy efficient. As a result, the cost of energy services has decreased. If a consumer had to spend all available income on commodity $x$, they could still buy the same amount. However, if a consumer had to spend all disposable income on service $s$, they could buy more of the services.

Under the new decreased cost for energy services, $s$, $a$ consumer will move the optimal choice from point A to point B and shift the bundle of choices to a new indifference curve, with a higher level of utility. The consumer will increase energy consumption from $s_A$ to $s_B$.

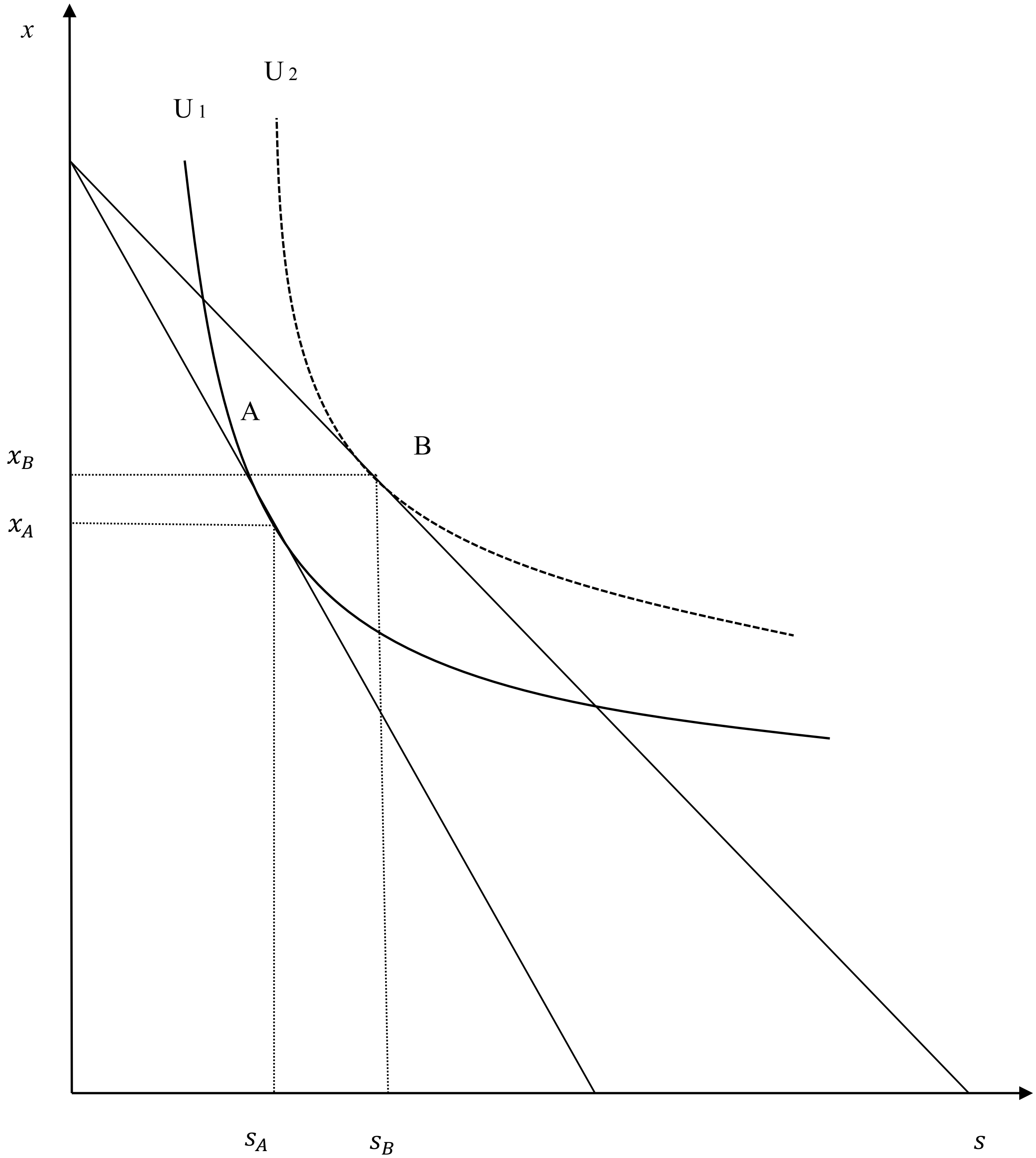



Figure 4: Consumer's total rebound effect

### 2.2.6 The producer of energy services

Typically, investments in EE involves spending more initial capital and achieving lower future energy operating costs. The initial investment cost is the difference between the purchase of a more efficient product and the cost of a conventional product, that provides the same services but requires a larger input of energy. The decision of whether it is preferable to invest in EE requires an assessment, in present values, of the initial cost of investments and expected future savings. However, comparing expected future energy expenditures to initial investment cost is a rather complex process. Expectations and assumptions must be stated in relation to future energy prices, discounting rates for future cash flows, changes to operation costs, the intensity of operation, and finally, a product's lifecycle. The decision for optimal investments in EE would minimize the present value of costs. This is described in the framework of a production function (Figure 5) where initial capital and energy consumption are viewed as inputs into the production of energy services.

An isoquant represents all factor combinations that are capable of producing the same level of output. Along an isoquant, the producer would be indifferent between combinations of input of capital (K) and energy (E). The cost-minimizing level of energy use is found at the point of tangency, where the marginal increase in capital cost, with respect to energy reduction, is equal to their relative price, in present-value terms. Producers of energy services may move along the energy-service isoquant by substituting capital for energy, in response to a change in relative prices. In those terms, isoquants are similar to indifferent curves of the theory of consumer's behavior. Figure 1 illustrates an example where relative prices change from $P_0$ to $P_1$. Both production choices provide the same units of outputs. However, as the producer moves from $P_0$ to $P_1$, the cost allocation between capital and energy changes. At $P_1$, the producer invests additional resources in the initial capital with an expectation to decrease energy costs.

As technology improves, the 'new' production function may shift the isoquant in a way favoring higher levels of EE. This is illustrated in figure6 where new production possibilities, available for the producer, are given in the isoquant 1. Typically, a lower isoquant would indicate a lower level of output. However, this is not the case with isoquant 1. Advances in technology make capital more energy efficient. Therefore, given the same amount of capital, less energy is needed to produce the initial output level.

This transition to a more efficient capital investment, is described in figure 7. As technology improves and innovative products enter the marketplace, the isoquant 0 shifts to the left. Initially, at isoquant 0, the producer minimizes costs at $(E_0, K_0)$. After the efficiency improvement in capital investments, the producer may achieve energy conservation by moving from $E_0$ to $E_1$. This however isn't an optimal decision choice for the producer. Realizing the benefits of the new production combination, the producer will eventually replace capital for energy because energy has become cheaper. The rebound effect is equal to $E_2$ - $E_1$.

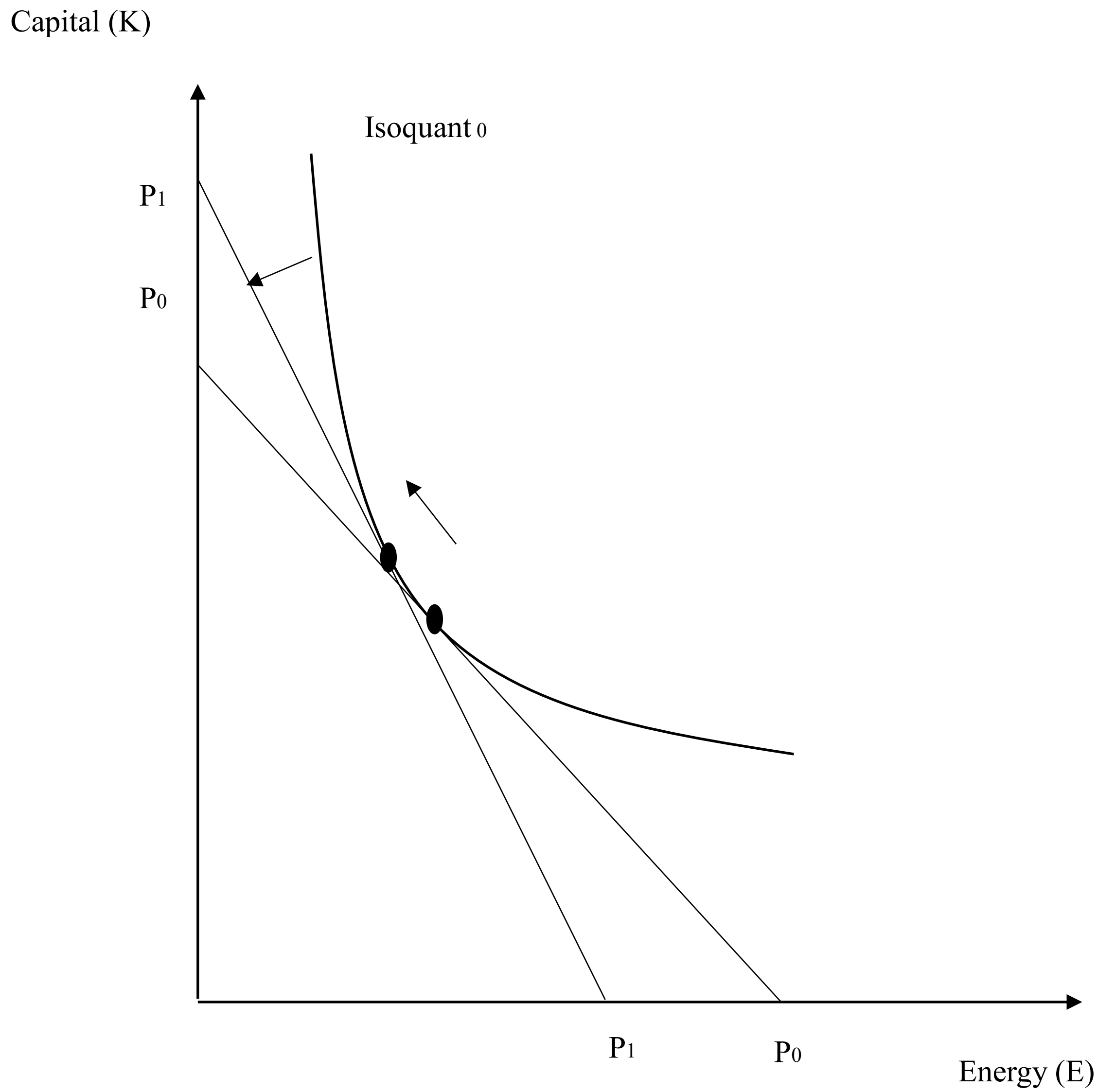



Figure 5: Producer's initial capital and energy consumption

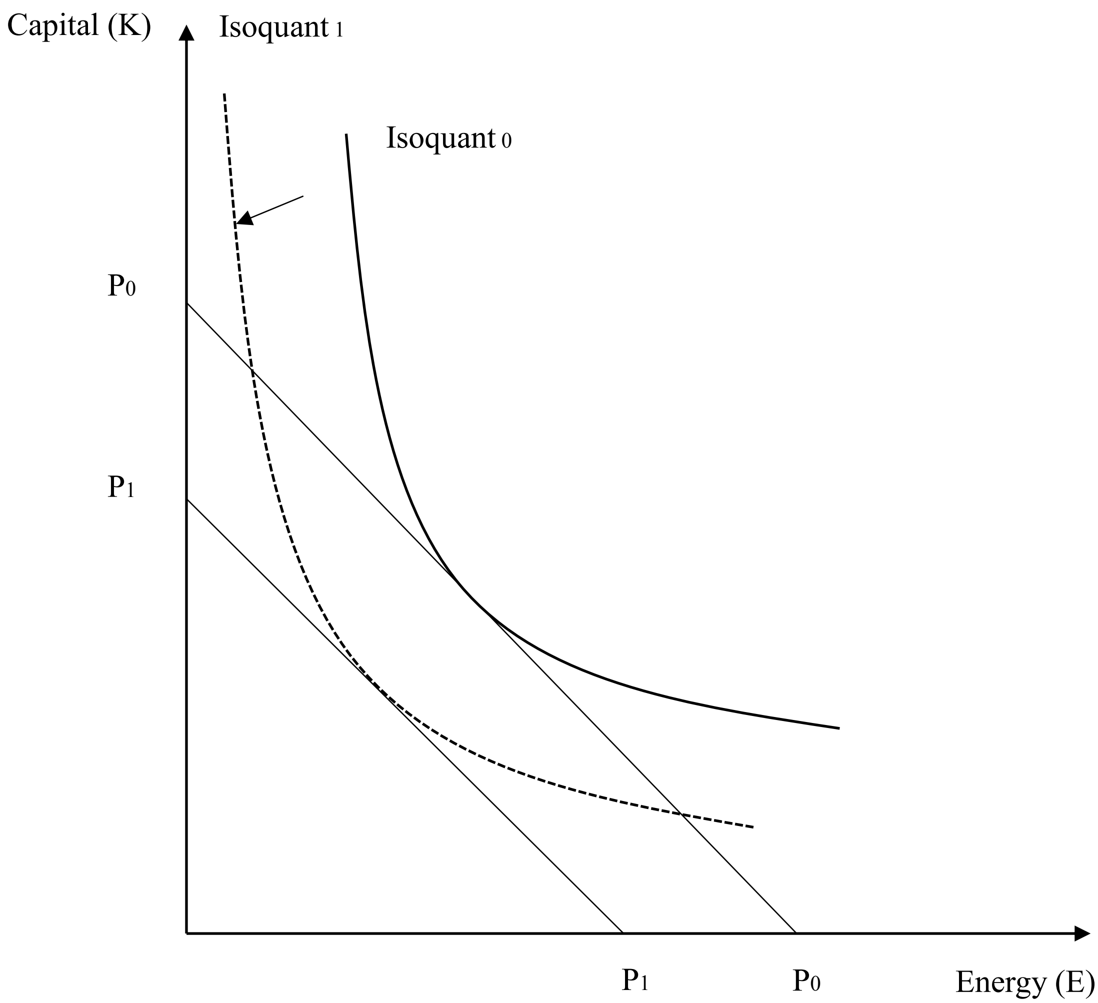



Figure 6: Producer’s improved capital and energy consumption

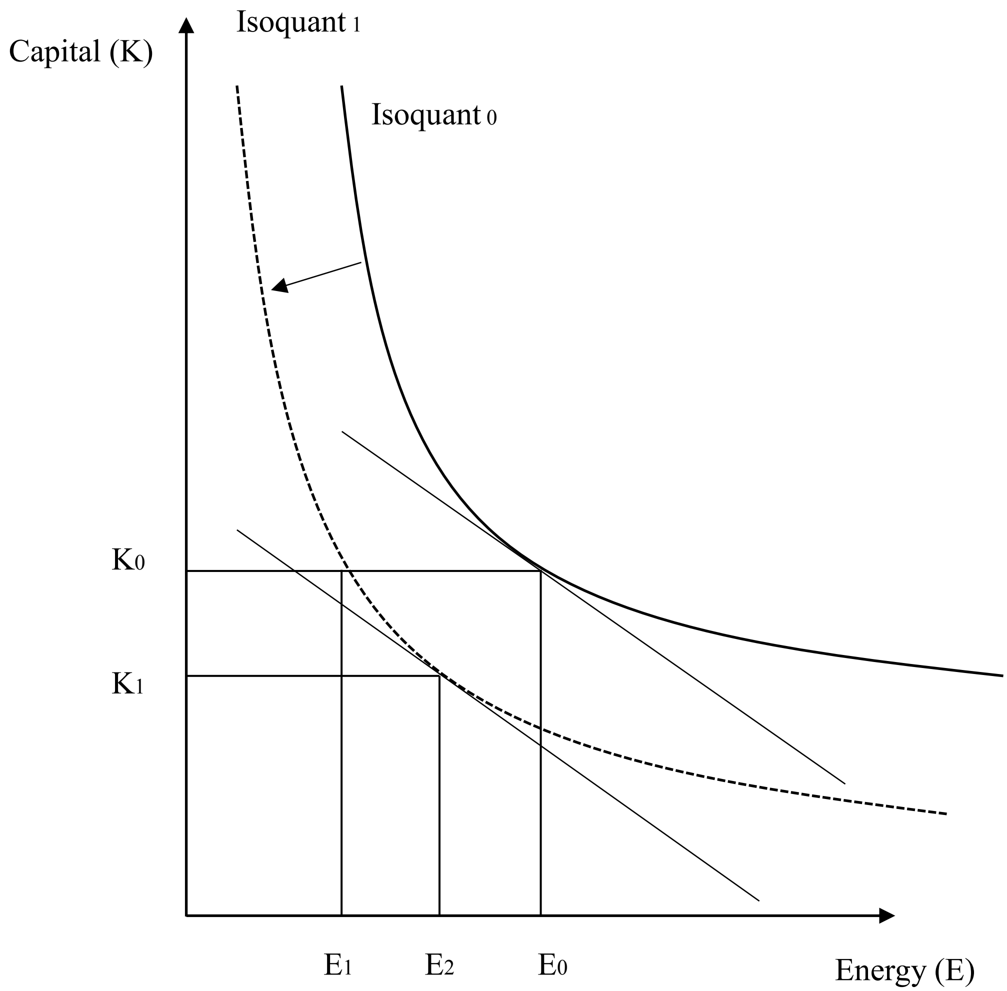



Figure 7: Producer's new capital and energy consumption

### 2.2.7 Welfare implications of the rebound effect

The welfare implications of the rebound effect are analytically discussed in the academic literature (Chan & Gillingham, 2015) (Borenstein, 2013) (Saunders & Tsao, 2012) (Gillingham & Palmer, 2014) (Otto, Kaiser, & Arnold, 2014). This section gives a brief summary of the theoretical conditions under which the rebound effect can be beneficial or undesirable. The analysis provided supports the basic economic concept that overall welfare is conditional on the relative costs and benefits of the additional service provided.

Using the notation already defined in the section of the direct rebound effect (2.2.3), the social welfare ($sW$) is defined as the aggregate utility used from the economic agents while accounting for negative externalities:

The social welfare is $sW = u(x, s_1, s_2) - ExC$ *(4)*

*ExC* represents the total externalities from the additional usage of energy services, and costs are given by $ExC = k(e_1 f_{11} + e_2 f_{22} + c_1 s_1 + c_2 s_2)$. Here, $k$ represents the population of identical consumers, $e_i$ represents the fuel's marginal external cost (e.g., from environmental pollution), and $c_i$ represents the service's marginal external cost (e.g., from traffic congestion).

Expression (4) does not account for the cost of the energy improvements. In case there is a cost associated with energy efficiency improvements, the net change in social welfare, on the margin, would be the difference between that cost and expression (4). Derivatives of the concept described are the following propositions:

Proposition 1: In the absence of negative external costs, an energy efficiency improvement necessarily improves social welfare.

Proposition 2: The direct rebound effect may increase or decrease overall welfare.

### 2.2.8 Welfare implications of energy efficiency improvements

The most commonly examined benefit of energy efficiency programs is a reduction in energy use. We assume that when doubling the efficacy of a lighting system, only half as much electricity is required to provide the same level of illumination. From this perspective, a less-than-proportional reduction in energy use is viewed as a failure of programs to increase energy efficiency.

However, it is often overlooked that an increase in energy efficiency can elicit changes in consumer's behavior such that an increase in energy efficiency does not lead to a proportional reduction in energy consumption.

This perspective ignores the fact that increasing energy efficiency also reduces the effective cost of energy services, which could elicit a behavioral response. For example, doubling automobile fuel mileage reduces the cost per mile traveled, and unless the price elasticity demand for automobile travel is zero, we can expect that more miles will be driven. A downward sloping demand for energy services implies this rebound effect. With the rebound effect, energy use is reduced less than in proportion to the increase in efficiency. However, there is also an increase in the energy services which also must be considered to be a social benefit.

Consider the example of replacing High-Pressure Sodium (HPS) highway lights with LED lighting in Rhode Island. LED lights provide an equivalent level of light while consuming 40-80% less electricity. In this specific example, the Rhode Island Department of Transportation, in cooperation with the RI Office of Energy Resources, chose a solution that lead to energy savings of 47%. This solution maintained, and in many cases, improved the previous levels of highway lighting. The improvement also implies that the energy investment in new lighting reduced 47% the effective energy "price" of providing highway lighting. Given the new lower effective price of lighting, the agency (RIDOT) might choose to improve highway safety by lighting previously dark sections of highways. In fact, soon after the completion of the lighting project in 2017, RIDOT decided to increase the hours of operation for the highway lighting. In the past, several areas of the road network were under a lighting 'curfew' between 1:00 AM and 5:00 AM. Realizing the benefits of the reduced operating cost, RIDOT removed the curfew.

For purposes of this example, suppose the agency increased highway safety by increasing the hours highway lights were on by 32%. The change in hours of operation implies that the amount of electricity consumed is reduced by 30% = (1-(1-0.47)*(1.32)) while simultaneously increasing public safety by providing better highway lighting. In this example, the rebound effect implies that electricity use is reduced less than proportional to the increase in energy efficiency (30% rather than 47%), but society also benefits from improved highway safety.

Therefore, the presence of a rebound effect does not imply a failure of energy efficiency programs, but rather it determines the extent to which social benefits are allocated among energy savings vs. increased energy services supplied. To properly evaluate the welfare effects of increases in energy efficiency, one needs to consider both energy savings and societal benefits from increased energy services.

Determining the sign of the ultimate welfare effect can be complex as it depends on the relative sizes of the values of energy services, fuel savings, and any external effects, such as pollution emissions and impacts on traffic. In some cases, such as automobile efficiency, external effects may be substantial, while in others such as highway lighting, external effects may be fairly small. But in general, many of these effects are difficult to quantify and express in monetary terms.

The most fundamental measurement when debating the merits of EE improvement in electricity, spurred by efficiency programs, is whether the rebound effect cancels the overall expected welfare implications. The question that arises next is: Why not conduct an analysis of energy efficiency policies by first examining the cost of the EE programs and then compare the net benefits including the rebound to the net gains? This is a valid question because as previously described in this study, net benefits of electricity EE programs such as expected energy savings may not be fully realized due to rebound effects. But as articles such as that of (Azevedo, 2014) have shown "There is still significant ambiguity about how the rebound effect should be defined, how we can measure it, and how we can characterize its uncertainty" (p.1). Other similar studies, with analogous findings, have contributed to increasing negative perceptions that these rebound effects may have. These results may influence decisions on future energy policies regarding EE programs. When there are large energy service externalities, as a result of the rebound, the social welfare is more likely to decrease with an improvement in energy efficiency. One classic example is traffic congestion in city centers.

In the case that the direct rebound effect and external costs of service are large, the energy efficiency improvements are more likely to decrease social welfare. Respectively, when the direct rebound effect and externalities are small, the energy efficiency improvements are more likely to increase social welfare. When this occurs and energy consumption increases, welfare may improve only if the consumer surplus from energy service consumption is greatly valuable (Chan & Gillingham, 2015). Despite such offsets, all findings that may affect policymakers' decisions to support new electricity energy efficiency policies must be evaluated in the general context of social welfare. In this context, it must be examined to what extent electricity EE improvements and their multiple goals are indirectly contributing positively to the overall welfare. For example, unlike the results of rebound effects in the case of the development and adoption of fuel-efficient automobiles, which increase the amount of miles driven and therefore traffic and accidents, electricity efficiency improvements such as public lighting, heating and air-conditioning lack such externalities (Alfawzan & Gasim, 2017). In recent publications, increasing importance has been given to the theory that EE programs have a fundamental impact on what is called multiple benefits outcomes that contribute to welfare-enhancing macroeconomic benefits. Depending on the magnitude of the rebound effect, these implications on social welfare fuel the human ambition to improve welfare and wealth (IEA, 2014). Nevertheless, the attempt to quantify the benefits and costs of the rebound effect in order to estimate their impact on the welfare implications of energy efficiency is very complicated. Researchers such as

Chan & Gillingham (2015), point out that the exact mechanism of how rebound influences the welfare implications of energy efficiency has "not been addressed in the literature" (p.25). There is a need for reasonable real-world estimates that take into consideration environmental externalities. According to the literature, quantifying environmental externalities is extremely difficult even when trying to access the welfare implications of the direct rebound effect in the driving habits of fuel-efficient automobiles (Parry & Small, 2005). For the purposes of this study, a brief description of four fundamental welfare implications is examined: energy security, health benefits, asset values, and disposable income.

**Energy security**

In the literature review of this thesis, the concept of energy security was introduced as a precursor to fundamental policy changes that lead to the dawn of EE programs for electricity. Today there is a modern concept of energy security that involves climate change and lays out the basic conditions for human prosperity. Some researchers like Gracceva & Zeniewski, (2014) claim that energy security is a product of the interactions and interdependencies of a complex system (Gracceva & Zeniewski, 2014). Gallagher & Appenzeller state that the energy system complexities are such ''whose properties are not fully explained by an understanding of its component parts'' (p. 89). Energy security, therefore, is a product of many diverse attributes, but some researchers like Ecofys (2009) have provided a three-tier categorization scheme: Extreme events, inadequate market structures, and supply shortfall. Out of the three categories of energy security risks as defined by Ecofys (2009), the latter two are well within EE program planning.

When EE improvements are well thought, they promote liberalization of generation resources that in turn create well-functioning, distortion-free electricity markets. Integrated power grids are also responsible for bringing to the consumer the best use of generation resources. It could be argued that even this improvement of supply stemmed from competition and increased customer choice may even provide resources for the first of the three categories of energy security risks mentioned above: Extreme events.

**Health benefits**

According to a study prepared by the Energy Efficiency Unit, Directorate for Sustainable Policy and Technology, of the International Energy Agency (IEA), there are well-documented benefits such as improved health and well-being (IEA, 2014). These benefits range from reduced respiratory disease symptoms to mental health impacts such as anxiety, stress, and depression. The worry alone about physical health well-being affects the overall health of citizens. More and better public lighting, for example, generates indirect positive social impacts that in turn reduce spending on public health budgets.

**Asset values**

High energy costs in the EU have prompted via European Union directives a multitude of electricity EE programs that were in turn eagerly adopted by consumers. Today, each building must display a plaque reporting the energy proficiency score. The properties that were made more efficient gained in value significantly. Respectively, similar trends are beginning to appear in the U.S. where an increase in property values. There is evidence that EE has a positive effect on both the sales and rental prices of properties (Hyland, Ronan, & Lyons, 2013).

**Disposable income**

It has been well documented that EE electricity programs benefit households that have access to a wider energy efficiency increase. According to Azevedo, (2014): If the energy efficiency measure being pursued saves money to the consumers over its lifetime, this means the consumer would actually experience a net increase in income. She might then use some of that income to increase her consumption of that same energy service, but the rest of it will be spent on other goods and services (or allocated to savings for future consumption). Some of these goods and services may have large energy or carbon footprint, whereas others will not (p. 6). However, in many (but not all) cases, more energy efficient appliances require a higher up-front investment, so there is a tradeoff between the cost of the appliance vs. energy use. But energy star appliances will typically be more expensive to purchase. Low-income individuals are likely to be at a disadvantage in the cases of higher upfront costs, even when energy saving pay off in the long run.

To reduce consumer expenditure of saved income on goods and services that have large energy or carbon footprint future energy efficiency policies could be drafted in such a way that would target decision making, for example, the offering of discounts on specific items such as more EE technologies.

The conclusion is that we know for a fact that EE improvements have a cost and consumption changes that can be both adding to the overall welfare or reducing the overall welfare. The impact of energy efficiency produces outcome at different levels of the economy. An investment takes place initially at the individual level in a household or in an enterprise. However, the outcome of EE impacts the economy as a whole. Targeted decisions at the individual level, as an outcome of EE incentive programs, may trigger developments in the local economy. Any future findings from research are bound to have important implications for policymakers.

## Chapter 3. Methodology

This chapter presents the methods used to analyze two empirical applications that examine energy efficiency (EE) incentive programs and concludes with the presentation of the methodology of the levelized cost of electricity and the datasets used.

The methodology analyzing the first empirical application was designed to examine the effectiveness of stated versus observed electricity savings, at the national level (US), as a result of EE incentive programs. The methodology of the second empirical application examines how an aggressive EE incentive program performs in comparison to moderate EE programs when implemented at the state level. A comparison between the methodologies of DiD and SCM is also employed. This chapter also presents the datasets used in the analysis and a brief presentation of the energy profile of the states used. Finally, the levelized cost of electricity is presented to provide a measure of comparison between the cost of renewable energy electricity supply and the cost of EE conservation.

### 3.1 First Empirical Application – National level analysis

The methodology of the first empirical application compares stipulated and observed energy savings due to the implementation of E.E. programs, at the national level. To identify whether there are discrepancies in the magnitude of the energy savings, that influence the cost of energy efficiency, the study aggregates the reported costs and savings of EE programs at the national level and estimates the weighted average cost of every unit of electricity saved. The reported values from this methodology represent the estimates that utilities provide using the analogical reasoning methodology to evaluate the impact in electricity consumption, using the engineering estimates of their programs.

As introduced in the theoretical framework section, the concept of analogical reasoning is utilized to explain the expectation that increasing spending on EE programs will deliver an analogous increase in energy savings. The reasoning by analogy approach is dominant in the energy market today and drives programs, policies, and expectations. In order to evaluate the validity of the reasoning by analogy approach, this research also assesses energy savings from the first economic principles angle, based on observed energy consumption.

3.1.1 Data sources of first empirical level

The data used for this empirical application are a collection of three large groups of time series. Energy data were obtained from the Energy Information Administration (EIA), demographic data from American Community Survey (ACS) and climate data from the National Oceanic and Atmospheric Administration (NOAA).

Monthly panel data for energy demand and prices of electricity were collected and analyzed for a period of eleven years, specifically from 2005 to 2015. Table 1 summarizes the program cost for implementation of EE programs for this period. The programmatic costs are divided as follows: customer incentives represent 55%, while other costs, including administrative expenditures, represent 45%. The share of funds dedicated to customer incentives appears to be increasing over time, which is encouraging to observe. In other words, the share of benefits provided directly to consumers in the form of cash payments, subsidies to appliances, energy audits and design services has increased in comparison to administrative, marketing, monitoring, evaluation costs, and utility-earned incentives. Table 2 provides insights into the cost of the expected incremental, annual savings of EE programs. However, there is no clear trend of the performance of the programs. The average cost for the examined period is $0.22 per incremental kWh saved. Some would expect that as program implementation develops, there would be an increase of the cost per kWh saved, as low-hanging fruit opportunities become exhausted. This outcome can be interpreted as an indication that across all states there are still opportunities for cost-effective investment in EE. Table 3 presents annual electricity total consumption for the same examined period, 2005 to 2015. Table 4 provides further insights into the distribution of electricity consumption between the residential, commercial and the industrial sectors. It is observed that there is a downward trend in the industrial share of electricity demand across the examined period. The residential sector accounts for the biggest portion of the total electricity demand during the eleven years (Table 4 and 5). Table 11 presents nation-wide average electricity prices for the same period in which the average cost per kWh remains stable at about $0.10. However, in figure 14, it is observed that demand differs significantly, creating four geographic clusters across the US.

Efficiency related savings were obtained by the EIA and are part of the information that electric utilities report via form EIA-861 to the federal government. This form captures energy efficiency data regarding programs implemented within every state. More than 700 utilities, representing 1/5 of the total number in the US, implement and report information related to the results of EE programs. Electricity savings are reported annually, for both incremental and total savings. Incremental annual savings, summarize the expected effect in demand, in terms of MWh for each utility, caused by new participants in existing programs, and all participants in new programs, during a given year. Reported incremental savings are annualized to reflect the program implementation effect if participants had initiated program participation on Jan 1. Within all programs, during a given year, in addition to the incremental effects, annual effects are also reported to reflect electricity savings achieved by existing and new participants. The effect is evaluated based on the start-up dates. For example, if participation took place on November 1st, only two months of savings are reported and reflect the useful life cycle of efficiency measures.

Since the year 2013, utilities have also reported life cycle incremental effects. The new variable reflects the number of years the program is planned to exist and includes all anticipated future savings, as well as reporting annual savings. For example, if a project has an anticipated life of 6 years, with savings during each year of 1,000 MWh, the reported incremental life cycle effect will be 6,000 MWh. For the period of the analysis, we observe that total annual savings are a multiple of the incremental savings with a multiplier that ranges from 9 to 10.6. This is an indication that electricity savings succeeded, in any given year, in having a more permanent impact.

The second dataset, demographic data, were collected to control for factors that may affect energy use. Population, GSP, type of housing, percent of vacant housing units, and percent of housing units that use electricity for heating. Table **23** presents the collected demographic variables.

The third dataset, climate data, were used to control for weather fluctuations. Since energy consumption depends on weather conditions, degree days were chosen to be used as the most common indicator to estimate demand for space cooling and heating. The variation of winter conditions is controlled for by heating degree days (HDD), and the respectively warm weather is controlled for by cooling degree days (CDD). Both indicators (HDD and CDD) are defined to a base temperature of 65° F, which is suitable for human comfort (Rosa, Bianco, Scarpa, & Tagliafico, 2004). Degree days are the number of degrees in Fahrenheit that deviates from the base temperature (65°F) as compared to a day's mean, outside air temperature. The amount of degree days is proportional to the amount of energy needed to heat or cool a building. The inclusion of heating and cooling degree days, in this model, as independent variables, control for weather fluctuation and the estimated coefficients of both variables are statistically significant.

In addition to the independent variables described above, the model specification in the regression includes panel fixed effects or each state that controls for climate differences among states and year fixed effects that capture annual weather trends. Both HDD and CDD variables are defined in a log-level relationship to the dependent variable. Energy intensity was logarithmically transformed when degree days are defined in degree units.

### 3.1.2 Modeling electricity saving reported from utilities

There is an extensive number of evaluation reports that estimate costs and electricity savings as a result of investments in energy efficiency. The U.S. Energy Information Administration (EIA) is the source of raw data for the majority of the studies. The EIA reports the performance of the EE programs based on data provided by utility companies, annually. The EIA is part of the U.S. Department of Energy and is the principal agency of the U.S. federal statistical system. In order to conduct this research, raw data from EIA were also utilized. The model is derived from weighted measures of average savings and costs and those datasets as reported by electric utilities (EIA Form-861).

This section frames the calculation of savings and costs based on the following notation. Let *n* index utilities such as *n*=1…N. Let *t* index years such as *t*=1…T. The *n*th electric utility reports savings (S) as a result of program implementation in *t*=1…$T_n$ years. However, not all utilities report savings in all 11 years. The same concept follows the notation for sales (D) and program costs (C). Electricity consumption that is reported before the utility invests in EE is reported MWh (0) and after the implementation MWh (1). Electricity savings are $S_{nt}$ and $MWh(1)_{nt} = MWh(0)_{nt} - S_{nt}$

To calculate the average per unit costs and savings, a weighted average measure was introduced following the equations (1) and (2). The results are reported in both discounted and non-discounted costs.

$$\textbf{Electricity Savings } (S) = \frac{\sum_{n=1}^{N} \sum_{t=1}^{Tn} (MWh(0)_{nt} - MWh(1)_{nt})}{\sum_{n=1}^{N} \sum_{t=1}^{Tn} MWh(0)_{nt}} \qquad (1)$$

**Energy Efficiency Program Costs** (C) = $\frac{\sum_{n=1}^{N} \sum_{t=1}^{T_n} C_{nt}}{\sum_{n=1}^{N} \sum_{t=1}^{T_n}(MWh(0)_{nt} - MWh(1)_{nt})}$ (2)

Equations (1) and (2) summarize the average weighted savings and costs from *n* utility over a period *T* and can be illustrated using a simple example. Suppose two utilities, *A* and *B,* spend (C) in year *t=1*, on Energy Efficiency programs, \$1 million and \$10 million, respectively. One year after implementing the program, utility A reports electricity savings of 20,000 MWh and sales of 900,000 MWh. Utility *B* reports electricity savings of 500,000 MWh and sales of 8,500,000 MWh. Following the notation described above, utility *A*: distributed $MWh(1)$ =900,000 MWh of electricity instead of $MWh(0)$ =920,000 MWh.

Accordingly, utility *B* distributed $MWh(1)$ =8,500,000 MWh of electricity instead of $MWh(0)$ =9,000,000 MWh. Based on the example above the estimated percent savings and costs per savings from utilities *A* and *B* are:

Percent electricity Savings (S) = $\frac{20{,}000\ MWh+500{,}000\ MWh}{11{,}000{,}000\ MWh}$= 4.73%

Energy Efficiency Program Costs per Savings (C) = $\frac{\$1{,}000{,}000+\$10{,}000{,}000}{20{,}000\ MWh+500{,}000 MWh}$= \$21.15 per MWh saved or 2.1 cents per kWh.

The above example is based on the assumption that $MWh(0)_{nt}$ is derived from the observed $MWh(1)_{nt} - S_{nt}$.

However, the above calculation which is based on utility stipulated energy savings, does not control for selection bias as described by Braithwait & Caves (1994) and is a principal economic concern that relates with subsidies (Hartman, 1988). Selection bias arises from the fact that treated individuals differ from non-treated for a reason or reasons other than treatment status. In addition, this modeling does not account for increased energy usage as a response to the reduced energy cost; the rebound effect (Gillingham, Rapson, & Wagner, 2015). Finally, this model omits to compare energy savings to an unbiased baseline which is essential to draw a meaningful conclusion. Due to all the above weaknesses, when ex-post assessments evaluate efficiency programs, the results tend to indicate that programs are constantly underperforming (Loughran & Kulick, 2004).

### 3.1.3 Modeling electricity savings using observed electricity consumption

This model assesses observed electricity usage and estimates the impact EE programs have on the reduction of electricity consumption, based on the econometric analysis. It evaluates how the observed electricity consumption differs after implementing an energy efficiency program for the ultimate purpose of assessing energy savings, which derive from an energy efficiency program. This analysis identifies if there is a solid ground for skepticism regarding the electricity reported savings and controls for the limitations described above. The model utilizes an observed, and easy to evaluate variable, electricity consumption, as a proxy for energy efficiency. However, the level of consumption without an EE program implemented is not observable. Therefore, it is necessary to construct an estimate of what the electricity consumption would have been without the EE program in place. This model forecasts energy consumption without the EE program in place, controlling for the number of customers, and the gross state product (GSP). In the developed econometric model, the dependent variable is the logarithmic transformation of electricity consumption and can be explained as energy intensity.

Panel data and fixed effects (FE) are introduced in analyzing the impact of the utility expenditure for rebates. Fixed effects allow the model to control for variables we cannot observe, or measure, such as behavioral or cultural, across states; and other variables that may change over time, but not across states, such as national and federal regulations. The analysis with FE panel data will also account for individual and household heterogeneity. The independent variables are the EE program cost, the energy cost, the average income, other demographics, and temperature in degree days. The study calculates the impact of utility spending for EE on overall energy consumption. The changes in electricity consumption are defined as:

$$\Delta MWh_{nt} = lnMWh(1)_{nt} \text{-} \; lnMWh(1)_{nt-1} \qquad (3)$$

and identified econometrically from specification described in equation (4)

$$MWh_{ijt} = \beta_1 \; EE_{ijt} + Y_{ijt}\beta_2 + X_{ijt}\beta_3 + Z_{ijt}\beta_3 + \mu_i + \nu_t + \varepsilon_{ijt} \qquad (4)$$

where:

$MWh_{ijt}$: is the log electricity sales for utility i located in state j in year t

$EE_{ijt}$: is the log expenditure for EE programs for utility i in state j in year t

$Y_{ijt}$: number of customers for utility i located in state j in year t

$X_{ijt}$: is a vector of utility − level covariates

$Z_{ijt}$: is a vector of state − level covariates

$\mu_i, \nu_t, \varepsilon_{ijt}$: Utility and year fixed effects- and potentially heteroskedastic error term.

The primary goal is to isolate the impact of EE programs spending on electricity demand, which is represented by $\beta_1$ in the equation above. Examining energy consumption, as the focus for addressing issues surrounding energy efficiency, is not something new. Studies have provided useful insights, introducing a methodology that utilizes energy intensity, to examine policies at the state level that have contributed to energy efficiency (Bernstein et al., 2003; Loughran and Kulick, 2004). Loughran & Kulick (2004), expanded the framework of Bernstein's et al., and introduced a more sophisticated econometric model. They concluded that expenditure for energy efficiency has a much smaller effect on energy consumption than utilities reported. The interpretation of $\beta_1$ is the effect of energy efficiency programs on electricity consumption and is the primary objective of this model. In the examined log-log regression specification of equation (4) the coefficient $\beta 1$ is an elasticity.

3.2 Second Empirical Application - State level analysis

The second empirical application examines the cost-effectiveness of state-specific EE programs. Traditionally, utility's revenues were completely dependent upon selling electricity. With decoupling programs discussed above in Section 2.1.8, energy pricing structures were revised to provide a mechanism for rewarding utilities for helping bring about energy conservation measures. Energy efficiency has great potential to meet energy demand at low cost, while simultaneously reducing may externalities, such as pollution emissions. A proper policy would increase investments in energy efficiency, starting with the most cost-effective energy efficiency actions, and proceeding to increasingly expensive actions until the marginal cost of reducing energy demand is equal to the cost of producing energy. Thus, the cost-effective policy is based on identifying the proper balance between reduced energy use and clean energy production. The second empirical application examines the cost-effectiveness of state-specific EE programs. The developed econometric methodology, for the second empirical application, compares whether there is a statistically significant difference between the efficiency performance of states with aggressive EE programs compared to states with moderate programs. For the purposes of this study, the State of Rhode Island was assessed as the state with the most aggressive EE program in the US and was compared to the states of New Hampshire and Maine, that have adopted moderate EE programs.

The differential effect of EE program implementation, also known as the treatment effect, is examined in the context of two econometric methodologies.

Specifically, the difference in differences (DiD) methodology and the synthetic control method (SCM) are implemented to evaluate effectiveness. Using the state of Rhode Island as the treated unit, both methodologies evaluate the impact of aggressive EE programs. A comparison between the methodologies of DiD and SCM is also employed to illustrate the methodological advantages of each method. The energy profile of the three states examined in the second empirical application, Rhode Island, New Hampshire and Maine, are presented in the following section.

### 3.2.1 State energy policy

States strive to provide reliable, cost-effective electricity sustainably. With these prerequisites in mind, they strive to deliver a safe, uninterrupted energy supply that meets the environmental standards of the communities they serve. Successful energy policy needs to promote cost-effective energy resources, to assist the production process, and enhance the well-being of the public. However, from a policy perspective, the situation isn't straightforward because reliable energy isn't always clean and clean energy is not always the least costly. Reliable energy supply is the one that is always available to meet demand needs. However, renewable energy, without storage, struggles to meet this definition of reliability, with the possible exception of hydropower. Wind and sun are not available on all days and at all hours of the year. A combination of renewable energy and energy storage is a promising solution that still has many limitations, both technological and financial. On the other hand, fossil fuels are reliable but are not clean, and are themselves finite resources.

The final factor to be consider is the cost. Energy resources are commodities that are subject to continuous price fluctuations. It is understood that the path to a reliable, clean, low-cost energy supply is dynamic. Technological and political interactions continuously affect the energy model for demand and supply.

This section examines EE electricity programs to provide insights into the expectations of energy policies on the demand side of the electricity market.

To achieve this, as explained previously, the electricity markets examined are in New England. Specifically, the states of Rhode Island, New Hampshire and Maine. All three operate under the same wholesale electricity market, the Independent System

Operator of New England (ISO-NE), which is an independent, nonprofit entity that serves six states: Vermont, New Hampshire, Maine, Rhode Island, Massachusetts, and Connecticut. ISO-NE's objective is to administer New England's wholesale electricity markets and provide services for reliability planning for the region's electricity system (ISO, 2017).

The states face very similar wholesale electricity prices, with minor differences resulting from transmission system conditions, such as line congestion and losses. Empirically, in this study, it was estimated that the magnitude of the difference in wholesale electricity prices, is less than 5%, across the three states.

This presentation of the state's energy profile contributes to the understanding of the energy efficiency policies that are implemented in the area with the highest electricity costs in the US. By examining a period of 11 years, from 2005 to 2015, and focusing on the state with the highest EE program spending in the US per capita, valuable insights are gained for the policy arena. Lastly, the specification of the methodology that is designed to examine three periods provides further information about the temporal performance of the programs.

### 3.2.2 State of Rhode Island energy profile

The Ocean State is the nation's smallest state and the second-most densely populated, after New Jersey. Located in the New England region of the Northeastern United States, it is the state with the second lowest per capita energy consumption in the nation, after the state of New York (Table 18: Total Energy Consumed per Capita, 2015 (million Btu). Rhode Island doesn't have any fossil fuel resources and is the state with the first offshore wind turbine installation in the US. The Ocean State's cutting-edge policies in energy go back to the 1990s. The state developed the first system benefit fund to lead efforts for demand-side management and renewable energy in 1993. The fund collected over $15 million/year, for energy efficiency, and created a new market for investments in RI's energy market. In 2006, the State of Rhode Island's General Assembly passed an energy bill known as "The Comprehensive Energy Conservation, Efficiency, and Affordability Act of 2006". The law contains an innovative condition as part of the state's principal least cost procurement mandate (R.I.Gen.Law.S39-1-27.7, 2016). According to the law, RI's approach to meet the state's energy needs is to prioritize investments in energy efficiency and energy conservation measures that are "prudent and reliable and when such measures are lower than the acquisition of additional supply."

The Comprehensive Energy Efficiency, Conservation, and Affordability Act of 2006 further transformed the energy efficiency market in Rhode Island. The concept of Least Cost Procurement (LCP) established new standards in energy efficiency investment decisions. The new objective is to implement EE investments on an economic basis rather than placing a cap on investments for budgetary or other purposes. The criterion for implementing an EE program is that the program be cost-effective. The cost-effectiveness is identified simply as the ratio of the net present value of the benefits to the net present value of the costs. The proposed EE programs, therefore, must have a cost lower than the cost of the acquisition of additional supply.

In practice, LCP required Rhode Island's utilities to invest in cost-effective energy efficiency that is less expensive than supply. The result is that 10 years later, RI is the state with the highest reported electricity savings due to EE programs in the nation, reporting statewide savings of 2.91% as a percent of 2015 retail sales - Table 24. To achieve these energy savings, RI utilities spent, for electric efficiency programs, $82.9 million in 2015, which represents 6.34% of the statewide electricity revenues. The proceeds that finance the program are a product of a surcharge that all consumers pay monthly, through their electric bill. Rhode Island spends a greater proportion of utility revenues than any other state on EE programs due to the LCP requirements. The energy efficiency plans are overseen by a stakeholder group, the Energy Efficiency and Resource Management Council (EERMC), with representatives from government agencies, environmental groups, businesses, and consumer advocates. The EERMC was created by the 2006 Act and is charged with the supervision of energy efficiency programs. It is funded through the billing surcharge and has 13 voluntary members. The governor, with input from the state Senate, appoints nine voting members with expertise in areas such as law, the environment, energy codes, and representatives of end-users. Four additional non-voting members represent the utilities and the delivered fuels industry. The Commissioner of Rhode Island's Office of Energy Resources serves as the EERMC's Executive Director and Executive Secretary. SEO staff provides the Council with administrative services. The EERMC meetings are scheduled monthly and are open to the public.

In addition to the EERMC, a stakeholder body, the Demand Collaborative, provides consistent and comprehensive contribution into the processes related to the delivery of

Least Cost Procurement. This group is convened by National Grid, which is the Rhode Island's largest utility, to solicit feedback on program plans and implementation strategies.

The EERMC has funding to retain independent, expert consultants that give technical assistance to Council members on LCP. The consultants provide research and recommendations that help the Council in decision-making, program improvement, and independent verification of the cost-effectiveness of the National Grid's plans.

| | |
|---|---|
| Direct Jobs in Energy Efficiency | 8,112 |
| Electric Program Expenditures | $84.73 million |
| Gas Program Expenditures | $21.5 million |
| Per capita Expenditures | $100.58 |
| Electric Savings | 214,512 MWh |
| Electric Savings as Percent of Retail Sales | 2.8% |
| Gas Savings | 4.1 million therms |
| Gas Savings as Percent of Retail Sales | 1.01% |

Table 1: Rhode Island EE profile (2015)

### 3.2.3 State of New Hampshire energy profile

New Hampshire is a state in the New England region of the northeastern United States bordered by Massachusetts, Vermont, Maine, and the Canadian province of Quebec. New Hampshire covers an area of 9,351 sq.miles and, as of 2013, has a population of 1.323,459 residents. The average state temperature is 46.3°F and has an annual snowfall of 61 inches. The state ranks 9th in the heating degree days in the nation (2015, Table 8). New Hampshire has no fossil fuels, petroleum, natural gas, or coal reserves.

The state's electricity generation is provided as follows: just over 2% by two coal-fired electric power plants, about 25% by natural gas power-plants and more than 15% by renewable energy. Almost half of the state's electricity generation comes from the Seabrook nuclear plant: the largest nuclear power generating unit in New England. The plant has a 1,244 MW generating capacity. Despite this output, per capita, residential petroleum consumption ranks among the highest in the US. This dependence is partially explained due to the cold winters. New Hampshire is a member of an independent, non-profit Regional Transmission Organization (RTO) named ISO New England Inc. (ISO-NE). The ISO-NE corporation oversees the entire New England power system. The state exports to its neighboring states nearly half of the electricity locally produced.

| | |
|---|---|
| Direct Jobs in Energy Efficiency | 6,833 |
| Electric Program Expenditures | $25.8 million |
| Gas Program Expenditures | $7.1 million |
| Per capita Expenditures | $24.79 |
| Electric Savings | 73,499 MWh |
| Electric Savings as Percent of Retail Sales | 0.67% |
| Gas Savings | 2.1 million therms |
| Gas Savings as Percent of Retail Sales | 0.70% |

Table 2: New Hampshire EE profile

**New Hampshire Energy Efficiency program**

In 2005, New Hampshire became one of the seven signatory states of the Regional Greenhouse Gas Initiative (RGGI). The New Hampshire Energy Efficiency program targets annual savings of 0.49%, of the electricity sales in 2015. The program funding according to the NH Statewide Energy Efficiency Plan is $26 million and the cost per lifetime kWh savings is $0.036. The program offered by NH electric utilities is funded by the System Benefit Charge (SBC), RGGI auction proceeds and revenues obtained by each of the NH electric utilities from the participation in the ISO-NE's forward capacity market (FCM). The SBC is less than 0.2 cents per kWh, five times lower than the SBC in Rhode Island (1.1 cents).

### 3.2.4 State of Maine energy profile

Maine is also located in the New England region bordering only with New Hampshire in the United States, and the Canadian provinces of Quebec and New Brunswick. Maine covers an area of 35,385 sq.miles, and as of 2016, has a population of 1,331,479 residents. Three-fifths (60%) of the state's population lives in rural areas, and it is the state with the lowest population density in New England. The average state temperature is 45.65°F and has an annual snowfall of 72 inches (US Climate data, 2017). The state ranks 6th in the heating degree days in the nation. More than five-sixths of Maine is still forested, and forest products are a major biomass resource, supplying wood-derived fuels such as wood pellets. Maine is the most petroleum-dependent state, for home heating, in New England (EIA, Primary Energy Consumption, 2015).

The state's electricity generation is provided as follows: Wind produces a little over 12%, hydroelectric dams 25%, and 25% is produced from biomass generators, using mainly wood waste products. In addition, over 30% of net generation comes from natural gas. The rest of Maine's net electricity generation comes from petroleum, coal, and solar power (U.S. EIA, Electric Power Monthly, 2015). Overall, 67% of Maine's net electricity generation comes from renewable sources. The state does not have fossil fuel reserves (petroleum, natural gas, coal).

Maine is also a member of ISO New England Inc (ISO-NE). Maine is one of the 12 States that allow combined heat and power as an eligible resource in EERS and renewable portfolio standard policies (Setting Energy Savings Targets for Utilities, 2011).

As far as load-serving entities (LSEs), the state of Maine has placed this obligation on a third-party non-governmental entity (Steinberg & Zinaman, 2014).

| | |
|---|---|
| Electric Program Expenditures | $45.5 million |
| Gas Program Expenditures | $1.1 million |
| Per capita Expenditures | $43.96 |
| Electric Savings | 166,500 MWh |
| Electric Savings as Percent of Retail Sales | 1.39% |
| Gas Savings | 148,346 therms |
| Gas Savings as Percent of Retail Sales | 0.14% |

Table 3: Maine EE profile

Maine Energy Efficiency program

In 2005, Maine, like New Hampshire, became one of the seven signatory states of the Regional Greenhouse Gas Initiative (RGGI). The Maine Energy Efficiency program targets annual electric savings of 20%, by 2020, with incremental saving targets of ~ 1.6% per year for 2014-2016 and ~2.4%, per year, for 2017-2019. Efficiency Maine operates under an all cost-effective mandate.

3.2.5 Difference in differences (DiD) methodology used in the second empirical model

The second empirical application explores whether energy consumption ($Y_{it}$) is affected by different levels of spending for EE programs ($D_{it}$). To determine this, the econometric methodology of the difference-in-differences (DiD) estimator was selected. The DiD is favored when estimating causal effects in empirical economics because the derived estimations from this research design offer an alternative to reach unconfounded measures by controlling for unobserved variables and combining it with observed or complementary characteristics. The DiD integrates the advances of fixed effects estimators with causal inference analysis when unobserved events, or characteristics, confound the interpretations (Angrist & Pischke, 2008). According to Villa (2012), DiD has been used "widely when the evaluation of a given intervention entails the collection of panel data" (p.2). It is also used even when panel data is not required, in its simplest version. According to Mora and Reggio (2013), only data from two periods are needed: "In the first period the pre-treatment period none of the agents are exposed to the treatment. In the second period, the post-treatment period those labeled as treated are already exposed to treatment while those labeled as "controls" are not" (p.2).

As stated by Lechner (2010), the DiD can calculate the results of an EE program intervention by using "the mean changes of the outcome variables for the nontreated over time and add them to the mean level of the outcome variable for the treated prior to treatment to obtain the mean outcome the treated would have experienced if they had not been subjected to the treatment" (p. 2). In our case, the specific intervention or treatment is the passage of a law by policymakers to subsidize EE. The model will then compare the difference in outcomes before and after the intervention for groups exposed to the intervention to the same difference in unexposed groups; the control group.

Card and Krueger's (1994) study in labor economics is a representative and well-known paper that demonstrates the DiD methodology. They collected employment data from fast food restaurants in New Jersey and Pennsylvania, in February 1992 and again in November 1992. The minimum wage in Pennsylvania stayed stable over this period. In New Jersey, the minimum wage increased. They used their data and the differences-in-differences methodology to estimate the effects of the increase of the minimum wage in employment. Pennsylvania's set of observations was used as a control group to identify the effects of the salary increase in the treatment – the New Jersey – observations. The idea of using DiD to study the effect of minimum wage levels on employment was introduced many years prior, by Obenauer and Von Der Nienburg (1915).

**DiD in the empirical application**

In this study, the observed value of residential energy consumption is $Y_{it}$ and can be assessed either as a control variable, $Y_{0it}$ or a treated variable $Y_{1it}$, depending on the treatment status. Status $Y_{0it}$ represents the non-treatment status for consumers served by utility (i) in period (t). It describes consumption in utilities with moderate EE program spending.

The different levels of spending for EE programs ($D_{it}$) are characterized as moderate or aggressive. This is a limitation of the method because it is applied to discrete, as opposed to continuous, levels of treatment. Another limitation is noted by Friedman

(2013), when referring to the working paper by Mora and Reggio (2013) in a post co-written by the two explains that: "DiD-as-commonly-practiced implicitly involves other assumptions instead of Parallel Paths, assumptions perhaps unknown to the researcher, which may influence the estimate of the treatment effect. These assumptions concern the dynamics of the outcome of interest, both before and after the introduction of treatment, and the implications of the particular dynamic specification for the Parallel Paths assumption."

**Fixed Effects**

Electricity consumption ($Y_{it}$) is also subject to fixed confounders $A_i$ such as behavior (fixed unit effects) and time varying covariates $\boldsymbol{X_{it}}$ such as income, electricity price and weather conditions. Term $\boldsymbol{\lambda_t}$ denotes year effects that are common across all observations in period t.

$E[Y_{0it}: A_i, X_{it}, t] = \alpha + \lambda_t + A'_i\gamma + X'_{it}\beta$ *(1)*

Assuming that the causal effect of the status of an EE program is additive and constant we have:

$E[Y_{1it}: A_i, X_{it}, t] = E[Y_{0it}: A_i, X_{it}, t] + \rho$ *(2)*

*Together equation (1) and (2) imply that observed residential electricity consumption in treatment group* $Y_{1it}$ is:

$E[Y_{1it}: A_i, X_{it}, t] = \alpha + \lambda_t + \boldsymbol{\rho D_{it}} + A'_i\gamma + X'_{it}\beta$ *(3)*

*Equation (3) implies that:*

$Y_{it} = a_i + \lambda_t + \rho D_{it} + X'_{it}\beta + \varepsilon_{it}$ *(4)*

*Where* $\varepsilon_{it} = Y_{0it} - E[Y_{0it}: A_i, X_{it}, t]$ *and* $a_i = \alpha + A'_i\gamma$

Differences in differences is a version of fixed effects estimation. In the case of EE programs, the notation is:

$Y_{1ist}$: Electricity consumption at utilities *i*, state *s*, time *t*, with aggressive EE program spending

$Y_{0ist}$: Electricity consumption at utilities *i*, state *s*, time *t*, with moderate EE program spending.

However, in practice, we only observe one or the other treatment status. The assumption is that in the absence of aggressive EE program budget change, energy consumption is determined by the sum of a time-invariant state effect $\gamma_s$, and a year effect $\lambda_t$, that is common across the examined states.

E[$Y_{0ist}$|s,t]= $\gamma_s + \lambda_t$ (5)

Let $D_{st}$ be a binary (dummy) variable for aggressive EE budget programs and periods. Assuming E $[Y_{1ist} - Y_{0ist}|s,t]$ = $\boldsymbol{\delta}$ is the treatment effect. Then observed energy consumption can be written:

$Y_{1ist}$= $\gamma_s + \lambda_t$+δ $D_{st}$+ $\varepsilon_{ist}$ (5)

The differences-in-differences strategy amounts to comparing the change in electricity consumption in areas with aggressive EE program spending, to the change in electricity consumption in areas with moderate program spending. Electricity consumption in areas with aggressive EE program spending (AG), before the implementation of the EE programs is described as:

E $[Y_{ist} \; | s = AG, t = 0] = \gamma_{AG} + \lambda_0$

The electricity consumption in AG after the implementation (t=1) is:

E $[Y_{ist} \; | s = AG, t = 1] = \gamma_{AG} + \lambda_1 + \boldsymbol{\delta}$

The difference between t=0 and t=1 is:

E $[Y_{ist} \mid s = AG, t = 1] -$ E $[Y_{ist} \mid s = AG, t = 0] = \boldsymbol{\lambda_1} - \boldsymbol{\lambda_0} + \boldsymbol{\delta}$

The electricity consumption in areas with moderate EE program spending (MI), is described as:

E $[Y_{ist} \mid s = MI, t = 0] = \gamma_{MI} + \lambda_0$

The electricity consumption in MI during treatment period (t=1) is:

E $[Y_{ist} \mid s = MI, t = 1] = \gamma_{MI} + \lambda_1 + \boldsymbol{\delta}$

The difference between t=0 and t=1 is:

E $[Y_{ist} \mid s = MI, t = 1] -$ E $[Y_{ist} \mid s = MI, t = 0] = \boldsymbol{\lambda_1} - \boldsymbol{\lambda_0} + \boldsymbol{\delta}$

There are two assumptions for unbiased DiD estimation in addition to OLS requirements:

1. There is a parallel trend in outcomes for both the control and treatment groups.
2. There is no spillover effect.

The parallel trend assumption is critical in the DiD model. It implies that in the absence of the intervention, both the control and treatment group would have the same differences in outcomes, over time. Visual observation of the outcomes in the pre-treatment period would assist in identifying appropriate control groups. However, this necessary condition does not indicate that the same trend will continue during or after the treatment period. Lastly, spillover effects can invalidate the use of the DiD methodology if the intervention in the treatment group may affect the control group.

### 3.2.6 Synthetic control method used in the second empirical model

Both the Synthetic Control Method (SCM) and the difference in differences approach, as described previously, aim to estimate the treatment effects of policy interventions that take place at an aggregate level, like a city or a state. While DiD assumes that the effect of unobserved confounders is constant over time, synthetic control tolerates confounders changing over time. Synthetic control was originally designed for case studies and is robust to the unobserved heterogeneity of confounders over time (Kreif, et al., 2016). The methodology used in synthetic control is to construct a control group that has similar pre-treatment features to the treated group. The method uses an optimized weighting procedure to get a better counterfactual for estimating the effect of an intervention.

The SCM model is specified as follows: Suppose there is one treated unit, i, and n control units, j (j = 1, 2 … n). We consider a policy intervention with data sampled both before, and after, treatment. The pre-treatment periods are $t = t_0, \dots, t_k$, and the post-treatment periods are $t = t_{k+1}, \dots, T$, so treatment happens between periods $t_k$ and $t_{k+1}$,. Let $Y_{it}$, denote an outcome in t for the treated unit, and let $Y_{jt}$ denote an outcome in period t for control unit j. **X** is a vector of predictors (covariates). For i, the treatment effect, $a_{it}$, is measured as the difference between its post-treatment outcome, $Y_{jt}$, and its synthetic post-treatment outcome, $Y'_{jt}$ . $Y'_{jt}$ is a convex combination of the post-treatment outcomes of control units, $Y_{jt}$, defined by optimized weights, $w'_j$,:

$$Y_{it} = a_{it} \cdot D_{it} + X_{it} \cdot \beta_i + \varepsilon_{it} \quad where\ D_{it} = \begin{cases} 0, t = t_0, \dots\dots, t_k \\ 1, t = t_{k+1}, \dots, T \end{cases} \quad (5)$$

$Y_t = X_{jt} \cdot \beta_j + \varepsilon_{jt}$ *and*

$$Y'_{it} = \sum_{j=1}^{n} w'_j \cdot Y_{jt} = \sum_{j=1}^{n} w'_j \cdot [X_{jt}\beta_j + \varepsilon_{jt}] \quad (6)$$

The treatment in the SCM model is the difference between the real treated unit, and its synthetic version, after the treatment as:

$$a_{it} = Y_{it} - Y'_{it} = Y_{it} - \sum_{j=1}^{n} w'_j \cdot Y_{jt} \quad \forall \text{ t} \geq t_{k+1} \quad (7) \quad \text{and}$$

s.t. $w'_j \geq 0$ and $\sum_{j=1}^{n} w'_j = 1$

The optimized weights, $w'_j$, are obtained by minimizing the distance M between $\mathbf{X_j}$, and $\mathbf{X_j} \cdot \mathbf{W_j}$ in the pre-intervention periods, according to:

$$\text{M} = \min_{w_j} [(\mathbf{X_i} - \mathbf{X_j} \cdot \mathbf{W_j})' \text{V} (\mathbf{X_i} - \mathbf{X_j} \cdot \mathbf{W_j})]^{\frac{1}{2}} \; \forall \text{ t} \in (t_{o,} t_k)$$

Where the matrix, V, is positive, definite and chosen to minimize the mean squared prediction error (MSPE) with respect to pre-treatment outcomes only, conditional on values of $wj*$. This process is what distinguishes SCM from a DiD approach, because control units are weighted according to the optimized $wj*$, instead of a simple weighting of $wj = 1/N$ (Wang, 2015).

### 3.2.7 Discussion of the econometric methodologies used in the second empirical model

The difference-in-differences methodology and the synthetic control method (SCM) are both used to assess the differential effect of a treatment on a treatment group versus a control group. In the context of this study, both methodologies evaluate the effect of a sharp increase of EE programs in energy conservation, at the state level. Difference-in-differences estimators provide unbiased treatment effect estimates when, in the absence of treatment, the average outcomes for the treated, and control groups, would have followed parallel trends, over time. This assumption is implausible in many settings.

The SCM evaluates treatment effects by constructing a weighted combination of control units, which represents what the treated group would have occurred in the absence of the treatment. While DiD estimation assumes that the effects of unobserved confounders are constant over time, the SCM allows for these effects to change over time, by re-weighting the control group so that it has similar pre-intervention characteristics to the treated group (Kreif, et al., 2016).

### 3.3 Levelized cost of electricity (LCOE) - Comparison

Energy efficiency investments are not implemented in a vacuum. Proponents always compare the avoided cost of electricity to the cost of generating energy. The objective is to determine whether energy efficiency investments are cost-effective. This section provides information about the relative cost of generating electricity using different technologies. The objective is to develop an understanding of how the cost per unit of electricity changes over time and more specifically on how energy efficiency compares to electricity generation from renewable resources.

The most common measure to compare different methods of electricity generation is the levelized cost of electricity (LCOE). The LCOE is the break-even cost of a unit of electricity in present-value terms, over the lifetime of a generating asset. It is estimated as the discounted sum of costs over the discounted sum of electricity produced over the lifetime of the investment:

$$\text{LCOE} = \frac{Sum\ of\ costs\ over\ lifetime}{Sum\ of\ electricity\ produced\ over\ lifetime} = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$$

Where the sum of the costs is the investment $(I_t)$ expenditures over the expected lifetime (n) of system, the operation and maintenance $(M_t)$ expenditures and the fuel $(F_t)$ expenditures in the year *t*, in present values using discount rate *(r).* The electricity $(E_t)$ generated over the lifetime of the generation is also discounted. The levelized cost of electricity is a convenient measure to compare different generating technologies. The lower the levelized cost the more competitive the generating technology is. Electricity generation using renewable resources, such as solar or wind, has no fuel costs and small variable $(M_t)$ operation and maintenance expenditure. The availability of financial incentives, including state or federal tax credits, can also impact the calculation of LCOE. The estimation of the LCOE is a projection, and there is uncertainty associated with the calculation. To estimate LCOE, we evaluate in present values a large number of future inputs and outputs based on a number of assumptions. This is the source of uncertainty. Also, the costs can vary regionally, and across time, as technologies evolve and fuel prices change. The limitations of the LCOE method are well known and documented in the literature. A recent report from the U.S Energy Information Administration (EIA, 2017) highlights that projected utilization rates, the existing resource mix, and capacity values are not taken under account in LCOE and a direct comparison of LCOE across technologies can be problematic. EIA proposes an additional assessment to determine the cost of electricity, the Levelized Avoided Cost of Electricity (LACE). EIA further suggests the evaluation of both measures to assess the economic competitiveness of various generation alternatives. However, LACE methodology is very complex and recent in literature. The added complexity, due to the absence of historical data, is the reason that LACE measures are not assessed in this section. Furthermore, it is not an objective of this research to compare the two methodologies that assess the cost of energy generated.

LCOE is a comprehensive tool and commonly cited measurement used to evaluate and compare different technologies that generate electricity. The numbers reported for the LCOE used in this research have value as a trend. The levelized cost of electricity may vary significantly across regions, and as already mentioned, is an estimated projection.

3.3.1 The LCOE of renewable energy resources

A presentation of the levelized cost of electricity (LCOE), for renewable energy resources, is used to develop an understanding about the cost gap between clean generation supply and energy conservation. The supply cost of electricity from renewable resources continues to decline in US, as wind remains the most cost-effective renewable technology. The utility-scale of solar photovoltaic (PV) technology demonstrates a higher rate of cost decrease.

The wind LCOE decreased 66% in the period 2009-2016. The same period, utility-scale solar LCOE decreased 85% (Lazard, 2016).

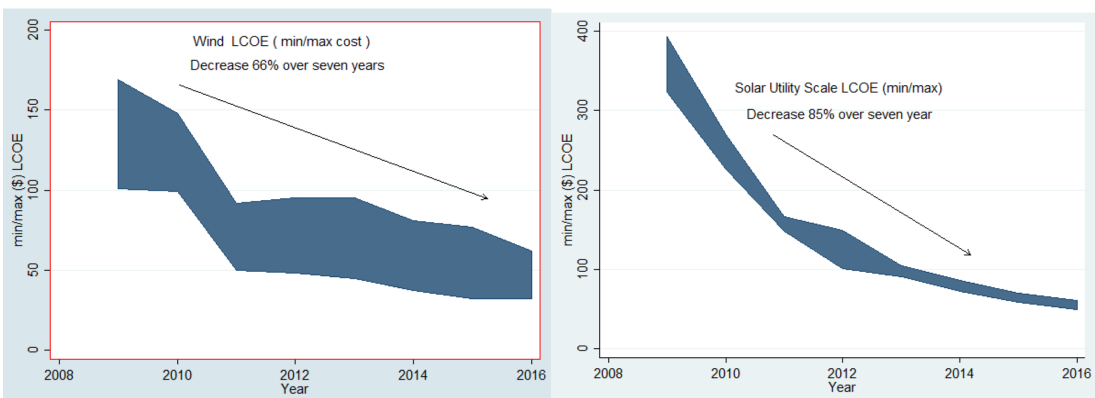



**Figure 8: Unsubsidized LCOE of wind and solar energy (2009-2016)**

Figure 8: Unsubsidized LCOE of wind and solar energy (2009-2016), demonstrates a clear picture of cost reduction for renewable resources. Even though renewable energy is increasingly cost-competitive, the cost has declined relatively modestly over the last five years for wind and rooftop solar. The LCOE decreases further with the inclusion of federal and state incentives. Table 4: LCOE - Renewable Resource (Lazard-2016) provides the range of the LCOE from renewable resources, based on the data provided from the investment bank, Lazard, in a study published in December 2016.

| Plant Type | Min per MWh | Max per MWh |
|---|---|---|
| Wind onshore | $32 | $62 |
| Solar PV – Residential Rooftop | $138 | $222 |
| Solar PV – C&I Rooftop | $88 | $193 |
| Solar Utility Scale (thin film) | $46 | $56 |
| Solar Utility Scale (crystalline) | $49 | $61 |

Table 4: LCOE - Renewable Resource (Lazard-2016)

The prices provided are based on an 8% cost-of-capital and a facility life-circle that ranges from 20 to 30 years.

In 2015, annual energy outlook, published by the EIA, provided LCOE for those plants going into service in the year 2020 (EIA, Annual Energy Outlook , 2016). Those projected prices are much higher than the LCOE provided by Lazard (2016).

| Plant Type | Min per MWh | Average per MWh | Max per MWh |
|---|---|---|---|
| Wind | $65.6 | $73.6 | $81.6 |
| Solar PV | $97.8 | $125.3 | $193.3 |

Table 5: LCOE - Renewable Resources (EIA-2015)

Data provided by the Advanced Energy Economy Institute (AEEI), dispute the EIA reported LCOE. The AEEI data conclude that the average power purchase agreement (PPA) for wind power was already at $24/MWh in 2013, and for the utility-scale solar PV, the price ranges from $50 to $75/MWh.

### 3.3.2 The LCOE of energy efficiency

The most comprehensive estimates, for the total cost of saving electricity, were published in a report by the Lawrence Berkeley National Laboratory (Hoffman, 2015). The report evaluates the electricity savings gained through energy efficiency programs that have been funded by ratepayers in 20 states. The report estimates that the U.S. average total cost of saved electricity, weighted by energy savings, was \$0.046 per kWh for the period 2009 to 2013. The median value for programs, with claimed energy savings across all sectors, was \$0.069 per kWh. The difference between the average and median reflects the fact that some programs delivered a large share of overall savings at a low total cost.

In the report by the Lawrence Berkeley National Laboratory, the total cost of saved energy is the total cost of the energy saved, spread in equal payments, over the economic life of the actions taken through a utility program, divided by the annual energy saved.

$$\text{LCOEE} = \frac{capital\ recovery\ factor*(total\ program\ administartor\ cost + participant\ cost)}{Gross\ Annul\ Energy\ Savings\ (kWh)}$$

Where LCOEE is the levelized cost of energy efficiency. The capital recovery factor is $\frac{A*(1+A)^B}{(1+A)^B-1}$, where A is the discount rate, and B the estimated program lifetime in years. The study used a 6 percent real discount rate as an approximation of the weighted average cost of capital for an investor-owned electric utility. The evaluation used claimed savings since program administrators do not report evaluated or verified savings.

## Chapter 4. Research Findings

4.1. First Empirical Application - National level analysis

From 2005 to 2015, utilities reported that EE programs saved 1.05% of the sample's annual electricity consumption, on average. During the same period, the EE programs had an average cost of $0.0396 per kWh, saved in nominal dollars, and an adjusted cost of $0.042 in 2015 dollars. In order to test the hypothesis of whether EE expenditures increased the energy efficiency of the US economy, we estimate the percent change in aggregate US electricity consumption due to aggregate expenditure on energy efficiency EE. Based on the econometric modeling assessed from this research, the savings produced by utilities are estimated to be between 0.48% - 0.75% of the sample's annual electricity consumption. The results imply a price elasticity of energy efficiency ranging between 0.29 - 0.54; indicating a rebound effect. This rebound effect implies that energy use is reduced less than proportionately to the increase in energy efficiency. It translates to an average cost of $0.051 - $0.06 per kWh saved, in nominal dollars, and an adjusted cost of $0.055 - $0.064 in 2015 dollars. The key finding is that utilities have been overestimating electricity savings and underestimating costs associated with EE incentive programs. The existence of a rebound effect suggests that energy savings are less than proportional to the increase in energy efficiency. However, consumers also benefit from an increase in energy services, since they get more of the service, at less cost to them. This claim is based on point estimates of average EE electricity savings and costs implied by an econometric model of electricity demand.

Electric utility companies have been implementing EE programs across the US for decades. During the past five years, we observe a strong positive trend in strengthening these programs by increasing their investments. EE programs' expenditure reached a high of $5.7 billion in 2015. The market of EE investments is estimated to be between $41 (IEA, 2017) and $63.7 (AEE, 2016) billion in revenue. Lighting is the largest segment and accounts for 39% of the total U.S. building efficiency revenue. The investments in HVAC equipment and in building envelop follow with 22% of the total revenues (AEE, 2016). A study in 2015, prepared by Booz Allen Hamilton for the U.S. Green Building Council, identifies that the green building sector supports over 2.3 million jobs and will directly contribute an additional 1.1 million jobs by 2018 (Hamilton, 2015).

The industry is growing rapidly. Furthermore, there is an almost universal belief that EE will not only reduce electricity consumption but will also decrease the environmental impacts of fossil fuels. As a result, policymakers approach the energy efficiency market as a 'win-win'; a success story that improves consumers' wellbeing while boosting the economy with large investments and the creation of new jobs.

The literature review section of this paper identified empirical evidence that EE programs promote cost-effective investments. The studies examined suggest that there is a strong statistically significant effect of EE programs on reducing electricity consumption. However, there is also an increasing concern that savings estimated by utilities are exceeding the actual performance of the programs. Moreover, the literature also highlights the rebound effect that can occur after the implementation of EE investments; when consumers realize decreasing electricity expenses, they tend to increase their consumption. In addition, selection bias reduces the effectiveness of the programs, as EE incentives do not always target end-consumers on the margin of doing EE. Instead, EE programs provide incentives to all consumers, many of whom would implement the investment even without the additional benefits of the programs ('free riders'). However, this transfer of funding to consumers that would have adopted the practices anyway has an ethical argument in favor. A transfer is not unwelcome since the program rewards those who adopt desirable actions, even if they didn't require the reward to adopt the action. In the pollution "offset" literature, this is referred to as "additionality"— actions that would be taken "in addition to" those that would happen without the program.

The argument is that the rebound effect and free-riders lead to the overestimation of the overall energy savings that result from program implementation. At the same time, it may be in the best interest of utilities to demonstrate higher-than-actual electricity savings, since EE programs are designed to compensate utilities based on the savings achieved by the programs. These factors can develop a gap between expected and realized savings from Energy Efficiency programs.

This chapter provides results that are consistent with the reviewed literature. The econometric model used in this paper suggests that EE expenditure does reduce electricity consumption. EE programs provide robust incentives to consumers and to businesses to overcome market barriers to the implementation of EE investments. Contemporary technological improvements and industrial automated production processes tend to reduce costs of new, improved and innovative efficient products. In this economic landscape, EE incentives seem to accelerate and promote investments in energy efficiency.

However, this analysis raises a concern about the magnitude of the effects of EE programs. This research indicates that observed savings are less than those reported by utilities,  which implies a cost of energy saved through EE is higher than that estimated by utilities, which has implications for cost-effectiveness of EE programs. This makes the creation of successful policy more complicated. Especially since policymakers and energy stakeholders generally believe that the industry needs additional incentives, particularly under the environmental threat of GHG emissions under the assumption that EE is the most cost-effective energy resource available (Yang & Yu, 2015).

### 4.1.1 Findings on reported electricity savings

In the examined period, 2005 to 2015, utilities reported that EE programs saved 1.05% of the sample's annual electricity consumption, on average. During the same period, EE programs had an average cost of $0.0396 per kWh saved in nominal dollars and an adjusted cost of $0.042 in 2015 dollars.

The number of electric utilities that participated in EE Programs for the same period is a subset of the total number of utilities. In 2005, 251 utilities that participated in EE programs reported incremental energy savings, from program implementation, that had an average annual cost of $5.01 million. Eleven years later in 2015, the number of electric utilities with active EE programs had doubled. It is worth mentioning that not only is there a significant increase in the number of electric utilities offering EE programs, but programs became more extensive. The average program cost increased from $5.1 to $9.76 million, a 95% increase. As a consequence, the total expenditure for EE programs for the year 2015 increased to $5.73 billion. This figure, when compared to the $1.26 billion that was spent in 2005, represents an increase of 355%, in nominal values. The total cost of program implementation can be divided into two categories: the financial incentives that are provided to end customers, and all other costs. Customer's financial incentives can be in the form of cash payments, subsidized tariff rates relative to non-participants, in-kind services like design work, and any benefits directly provided to end customers for their participation in a program. Before 2010, the "other costs" category was reported in terms of direct and indirect costs to the utility. Annually reported program expenditures by group of expense and by state are presented in Table 7: Annual Costs of Electricity Efficiency Program Implementation.

For the examined period, annual nation-wide electricity sales follow a flat trend. Utility annual sales, revenues, number of customers and number of utilities that were in business, are presented in Table 9: Annual Electricity Consumption in US. Electricity sales to residential, commercial and industrial customers are depicted in Table 10: Electricity consumption by Sector in US (MWh). Based on the data presented, there is a notable reduction in the industrial sector's demand for electricity, from 27.79% in 2005 to 26.24% in 2015. During the same period, the residential sector's share was stable and flat while the commercial sector's share increased from 34.89% in 2005 to 36.20% in 2015. The number of utilities that provided services in the examined period fell from 3,541 utilities in 2005 to 3,212 in 2015, a 9.3% decrease.

The reported, incremental, annual, average electricity savings increased from 23,421 MWh in 2005, to 44,615 MWh in 2015. In addition, for the last three years of the period examined, 2013 to 2015, utilities started to report lifecycle electricity savings from implemented programs. The ratio of incremental to lifecycle savings provides information about the weighted average in years of savings achieved by a program's portfolio. For the period 2013 to 2015, this ratio was 10.9 years. This means that, on average, the impact of program implementation will result in energy savings for a period of about 11 years from the date of intervention.

The weighted average electricity savings (S) as a percent of electricity consumption for EE programs implemented for the examined period are:

$$(S)=\frac{\sum_{n=1}^{N}\ \sum_{t=1}^{Tn}(MWh(0)_{nt}-MWh(1)_{nt})}{\sum_{n=1}^{N}\ \sum_{t=1}^{Tn}MWh(0)_{nt}}$$

Which equals 1.05% of the associated electricity consumption. Program costs can be expressed as:

$$(C)=\frac{\sum_{n=1}^{N}\ \sum_{t=1}^{Tn}C_{nt}}{\sum_{n=1}^{N}\ \sum_{t=1}^{Tn}(MWh(0)_{nt}-MWh(1)_{nt})}$$

which is the weighted average cost per kWh saved (reported by utilities); \$0.0396 in nominal dollars and a adjusted cost of \$0.042 in 2015 dollars.

### 4.1.2 Findings on econometric modeling to derive electricity savings

In order to test the hypothesis of whether EE expenditures increased the energy efficiency of the US economy, we estimate the percent change in aggregate US electricity consumption due to aggregate expenditure on EE. From 2005 to 2015, based on the econometric modeling presented in the methodology chapter, the savings produced by utilities are estimated to be between 0.48% - 0.75% of the sample's annual electricity consumption. The results imply a price elasticity of energy efficiency in the range of 0.29 - 0.54. This is an indication of a rebound effect. Based on this estimation, the EE programs had an average cost of  $0.051 - $0.06 per kWh saved, in nominal dollars, and an adjusted cost of $0.0551 - $0.0648 in 2015 dollars. The performed analysis is based on models described in the methodology section. The essence of the concept is that while we can observe electricity consumption after the implementation of an EE program, we cannot observe what the demand for electricity would have been in the absence of the program. For this reason, we used econometric modeling to construct an estimate of electricity demand, as it would have been without the EE programs. For this purpose, four specifications are presented in Table 19: Effect of EE programs in Electricity Consumption, to better describe the relationship between electricity consumption - $MWh_{nt}$- and expenditures for EE programs. The dependent variable is the logarithmically transformed electricity consumption, the difference of which -

$$\Delta MWh_{nt} = lnMWh(1)_{nt} - lnMWh(1)_{nt-1}$$

represents a percent change in consumption.

The regression specification is identified by equation (5) as:

$$MWh_{ijt}=\beta_1 EE_{ijt} + Y_{ijt}\beta_2 + X_{ijt}\beta_3 + Z_{ijt}\beta_3 + \mu_i + \nu_t + \varepsilon_{ijt} \qquad (5)$$

Where the dependent variable ($MWh_{ijt}$) is the logarithmic sales of electricity for utility (i), in state (j), in year (t). $EE_{ijt}$ is the logarithmic EE program cost. The estimate of the coefficient $\beta_1$ is an elasticity of energy consumption with respect to expenditures on the energy efficiency program. The interpretation of $\beta_1$ is the effect of energy efficiency programs on electricity consumption and is the primary objective of this application.

$Y_{ijt}$ controls for the number of customers for utility i, in state j, in the year t. $X_{ijt}$ is a vector of utility level covariates and $Z_{ijt}$ is a vector of state level covariates. The $\mu_i, \nu_t, \varepsilon_{ijt}$:are utility and year fixed effects and the potentially heteroskedastic error term.

Taking first differences of equation (5) we estimate:

$$\Delta_t MWh_{ij} = \beta_1 EE_{ijt} + \Delta_t\, Y_{ij}\beta_2 + \Delta_t\, X_{ij}\beta_3 + \Delta_t\, Z_j\beta_4 + \Delta_t\, \nu + \Delta_t\, \varepsilon_{ijt} \quad (6)$$

Where $\Delta_t$ is the first difference of electricity consumption in period t and (t-1):

$$\Delta_t MWh_{ij} = MWh_{ijt} - MWh_{ijt-1}$$

The specification (5) includes year fixed effects to control for changes that are common to all utilities. The coefficient $\beta_1$ *on* $EE_{ijt}$ in equation (5), is a measure of the effect of EE program cost, at the utility level, on electricity consumption. The model specification controls for covariates that vary over time within states and utilities. At the utility level, time-varying variables include the number of customers that each utility services, and the sales share of Commercial and Industrial sectors. State time-varying covariates include the cost of electricity, weather conditions in terms of cooling and heating degree days, gross state product, and the cost of natural gas and housing characteristics.

The results of the econometric model are presented in Table 19: Effect of EE programs in Electricity Consumption. These results show that for the period 2005-2011 the EE expenditure is statistically significant, at better than 1% ($p<0.01$), with the expected negative sign. As utilities increase EE program costs, electricity consumption decreases. The coefficient for the number of customers and the degree days is positive and statistically significant. The magnitude of the coefficient for cooling degree days is higher than the one for heating degree days. This indicates a stronger relationship between electricity consumption and cooling needs. Electricity price has a negative sign in models 3 and 4 but is statistically significant at $p<0.1$ only in model 3. Model 4 includes year fixed effects.

## 4.2 Second Empirical Application - State level analysis findings

This section addresses the effectiveness of energy efficiency programs in reducing energy consumption, using data at the state level. In the examined period, 2005 to 2015, the second empirical application assessed the most aggressive, in terms of expenditure, EE program in US, the electricity EE program of Rhode Island. Two distinct methodologies, the DiD, and SCM compare Rhode Island's residential electricity consumption per customer with a counterfactual estimate. Here, counterfactual means "what would have occurred without an aggressive EE program in place."

This section applies the difference in differences and synthetic control method to assess the effectiveness of energy efficiency programs in reducing energy use at the state level using observational data from states in New England. This methodology evaluates program performance between states with dynamic EE investment policies and states with moderate investments in EE programs.

Findings from the comparative case study using the SCM, suggest that electricity sales in Rhode Island fell after the implementation of an aggressive EE program in 2008. However, the estimate of reduction is less than expected and reported by utilities. This difference is consistent with the findings of the first empirical application. The second methodology, using DiD, compared the performance of the residential electricity EE program of RI with that of NH and ME. The study identified that there is not a statistically significant effect on residential consumption, as a result of the substantial increase in EE expenditure in RI during the period 2008 to 2015, relative to NH and ME, states with more moderate programs.

The main objectives of states' energy policies are to provide a reliable, clean and low-cost energy supply. Energy efficiency (EE) programs, funded by ratepayers, influence this objective by supporting the concept that the cheapest energy is the energy you don't produce in the first place. This section examines the question of whether high-intensity EE programs, as expressed with the adoption of aggressive spending, contribute to proportionately larger energy savings. The scenario being examined describes the situation where the cost of electric EE programs increases significantly - by a factor of 2 or higher, as an outcome of changes in policy. In this case, stakeholders expect the observed electricity consumption to follow a different trend, to decrease, in comparison to the pre-intervention period.  However, the outcome of the intervention may not result in a clear change in consumption. In this case, program administrators may assume that there is another effect in play; an increase in consumption was avoided. Under the second scenario, the absence of an observed counterfactual creates uncertainty in the identification of a program's effectiveness. The goal of this chapter is to identify if a continuous increase in EE incentives will bring the desired and expected policy outcomes.

4.2.1 Difference in differences methodology

In the examined period, 2005 - 2015, the second empirical application assessed the energy efficiency policy of Rhode Island and compared its outcome to Maine and New Hampshire. Findings suggest that there is not a statistically significant effect in residential consumption as a result of the substantial increase in EE expenditure in RI during the period 2008 to 2015.

Specifically, the DiD methodology was employed to identify if a legislative act known as Least Cost Procurement (LCP) that established new standards in energy efficiency investment decisions affected the residential electricity consumption in Rhode Island. Rhode Island's least-cost procurement policy requires that energy demands be met in a manner that is cost-effective, reliable, prudent and environmentally responsible. The same policy also permitted an increase in EE program expenditures from about 2% of total annual electricity revenues, to about 7% by the year 2013, making RI the state with the most aggressive EE program in the US.

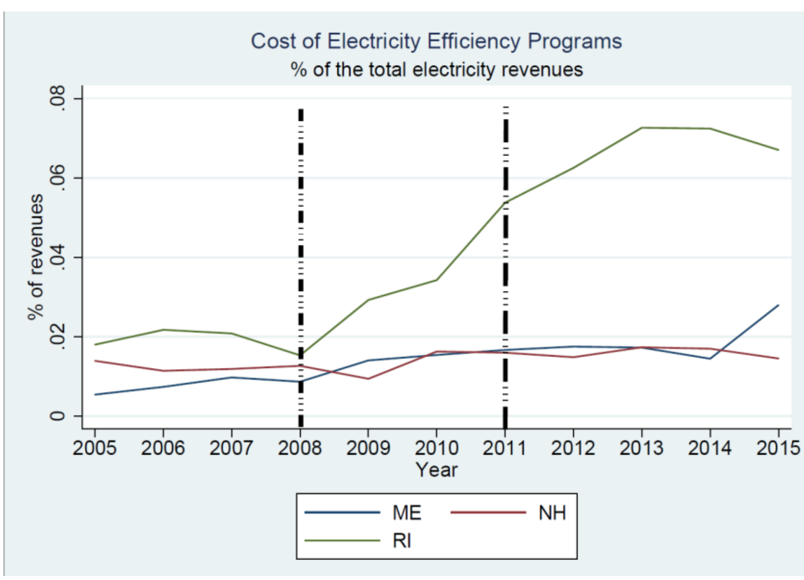



Figure 9: Cost of Electricity Efficiency Programs

Treatment is defined by the magnitude of the cost of the EE program spending as a percentage of total electricity sales revenues. Initially, utilities were grouped into discrete groups (D) based on their spending on EE programs. The lowest percent of expenditure for EE programs was chosen to serve as the control group. Then, instead of using the two-period model, effects are estimated in three periods. 1) pre-implementation (PI), in which utilities have approximately the same level of EE program spending, 2) post-implementation first phase (PI1P), which is after the announcement of a substantial increase in the expenditure on EE programs. This is the phase with higher expected savings, and 3) post-implementation second (PI2P); this is the phase of implementation with lower expected savings.

The model described allows for two treatment periods, PI1P and PI2P, to have a differential impact on electricity intensity. PI1P, the intermediate period, may include low hanging fruit savings and behavioral impacts, while savings for the P12P period may include more comprehensive, deep savings that are less cost-effective. The specification is:

$$\ln(c_i) = \sum_{k=2}^{G} \alpha_k \, group_{ki} + \beta_1 \, PI1P_i + \beta_2 PI2P_i$$

$$+ \textstyle\sum_{k=2}^{G} \gamma_{1k} \, group_{ki} \, PI1P_i + \sum_{k=2}^{G} \gamma_{2k} \, group_{ki} \, PI2P_i + \, X_i{}'\delta + \varepsilon_i \qquad (1)$$

is the electricity consumption in utility i$c_i$$group_{ki}$, equal to one, if an EE program in utility i is within the $k^{th}$ $PI1P_i$ $PI2P_i$ , equal to one, if consumption occurs in period $PI1P_i$$PI2P_i$ $X_i$ number of residential customers, price of electricity, state specific GDP, heat and cooling degree days, housing characteristics and share of electricity in heating methods. $X_i$ control group in time period PI.

Finally, $\varepsilon_i$

ents are interpreted as follows: $\alpha_k$ $\beta_1$ $\beta_2$ $PI1P_i$ $PI2P_i$ $\gamma_{1k}$ $\gamma_{2k}$, and measure, for $PI1P_i$ respectively, the differential change in residential electricity consumption from the pre-announcement time period for group k relative to the change in consumption of the control group.

Table 20: Difference in differences estimate of the EE program spending, presents the causal inference estimates for the effect of EE programs on RI residential electricity consumption. There are four different columns that represent four different models. All four models utilize panel data over a period of 11 years, in three states (RI, ME and NH). The dependent variable is the logarithmic transformation of residential electricity consumption, reported from each utility $\ln(c_i)$.

The set of coefficients is described in Table 20: Difference in differences estimate of the EE program spending, under the section Difference-in-Differences corresponding to $\gamma_{1k}$ and $\gamma_{2k}$ in equation (1) represents the coefficients of interest. They measure the differential change in residential electricity consumption in two periods, T1 for period $PI1P_i$ and T2 for $PI1P_i$, for RI utilities relative to the change in consumption of utilities in ME and NH in the period before the year 2008. The coefficients under the DT1 description correspond to $\gamma_{1k}$ coefficients of equation (1) and describe the interaction terms between the treatment group (RI utilities) and the first treatment period, years 2008-2010. All coefficients have a negative sign but are statistically insignificant. The same negative sign and statistical insignificance are seen on the coefficients corresponding to $\gamma_{2k}$ for period T2, years 2011 to 2014.

Figure 10: Residential Electricity Consumption Index (ME, NH, RI), provides an insight into the residential electricity consumption for a period larger than the already examined. The objective of the index is to provide, in a comparative framework, the trend of electricity consumption. Having as the base year, 2005, we observe how electricity consumption changes, annually, through year 2016. The treated unit, the state of RI, and the control states followed similar trends, over the examined period.

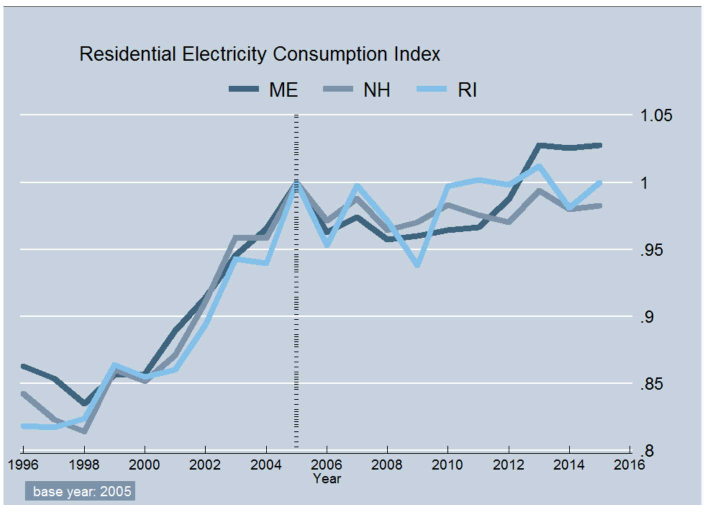



Figure 10: Residential Electricity Consumption Index (ME, NH, RI)

The Figure 11: Residential Electricity Consumption kWh (ME, NH, RI) – represents the trend of the annual residential electricity consumption per consumer for the period of the study in kWh.

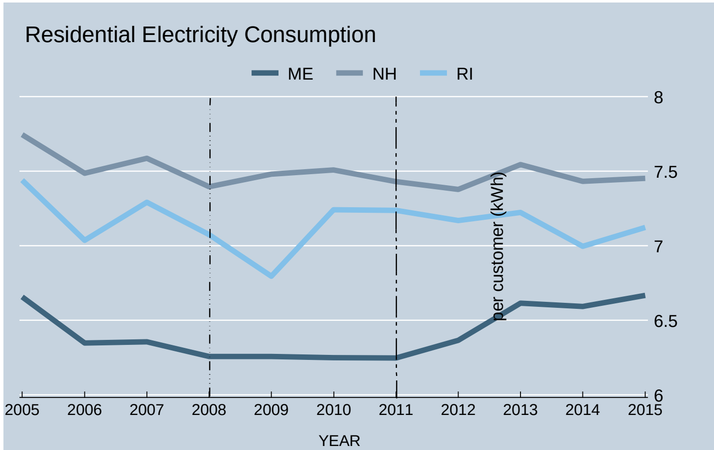



Figure 11: Residential Electricity Consumption kWh (ME, NH, RI)

Table 6: Pre and Post Treatment Differences of RI, NH, ME (2005-2015)

| Year | Rhode Island | New Hampshire | Maine | Diff. RI-NH | Diff. RI-ME |
|---|---|---|---|---|---|
| 2005 | 7.439 | 7.744 | 6.658 | -0.305 | 0.781 |
| 2006 | 7.036 | 7.486 | 6.348 | -0.450 | 0.688 |
| 2007 | 7.292 | 7.586 | 6.357 | -0.295 | 0.935 |
| 2008 | 7.074 | 7.395 | 6.258 | -0.321 | 0.816 |
| 2009 | 6.796 | 7.479 | 6.257 | -0.683 | 0.539 |
| 2010 | 7.240 | 7.508 | 6.249 | -0.268 | 0.991 |
| 2011 | 7.237 | 7.429 | 6.247 | -0.192 | 0.989 |
| 2012 | 7.168 | 7.378 | 6.367 | -0.210 | 0.801 |
| 2013 | 7.222 | 7.544 | 6.615 | -0.322 | 0.607 |
| 2014 | 6.996 | 7.432 | 6.593 | -0.436 | 0.403 |
| 2015 | 7.123 | 7.452 | 6.668 | -0.329 | 0.455 |

### 4.2.2 Synthetic control method (SCM)

We apply the synthetic control method to study the effects of the Least Cost Procurement (LCP) legislation in RI. LCP required Rhode Island's utilities to invest in cost-effective energy efficiency that is less expensive than supply. Large-scale investments in EE programs started, in RI, in 2008. Using the techniques described in Chapter 3, we construct a synthetic Rhode Island, with weights ($W$) chosen such that the constructed synthetic Rhode Island best represents the values of the predictors of electricity consumption for residential customers in Rhode Island in the pre-implementation period. Subsequently, cross-validation technique was introduced to choose the weights $u_m$ in Equation: $\sum_{m=1}^{k} u_m (X_{1m} - X_{0m}W)^2$

where $u_m$ is a weight that reflects the relative importance assigned to the *m-th* variable (*X),* when we measure the discrepancy between $X_{1m} - X_{0m}W$.

Synthetic controls must closely reproduce the values that variables with large predictive power, on the outcome of interest, take for the unit affected by the intervention. Accordingly, those variables should be assigned large $u_m$ weights. In the empirical application below, we apply a cross-validation method to choose $u_m$.

We use predictors measured in the pre-implementation to select the weights $u_m$, such that the constructed synthetic control minimizes the root mean square prediction error (RMSPE).

Initially, SCM is applied to a single treated unit, the state of RI. Each synthetic version is constructed with weights from a pool of control states. Predictors include demographic variables, income and lagged dependent outcomes. Figure 12 displays annual per-residential-customer electricity consumption for Rhode Island, and its synthetic counterpart, from 2005-2015. Table 26 displays the weight of each control state in the synthetic Rhode Island. The weights reported in table 27, indicate that electricity consumption trends in RI, prior to the passage of LCP, are best reproduced by a combination of New Jersey, New York, Pennsylvania, and Vermont. The remaining states, in the donor pool, were assigned zero weights (*W*). The weights assigned to state donors, combined with the high balance on electricity consumption predictors (Table 28), created a synthetic Rhode Island that provides an estimate to the per customer electricity consumption that would have occurred, in the absence of the LCP legislation. The developed SCM provides a methodical approach to estimate this counterfactual; the state of RI after the year 2008.

In 2008, residential electricity consumption decreased markedly, in RI, relative to a comparable synthetic control region. We estimate that, by the year 2015, annual per-consumer residential electricity consumption in Rhode Island was 97 kWh lower, on average, than what it would have been in the absence of LCP.

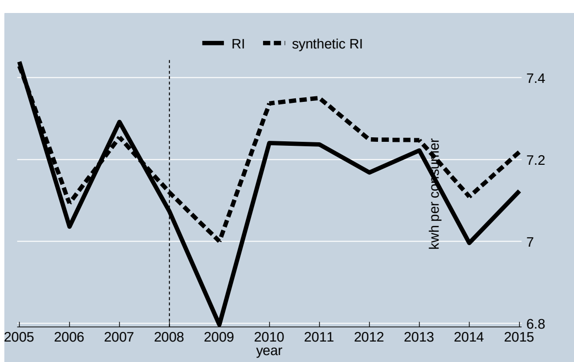
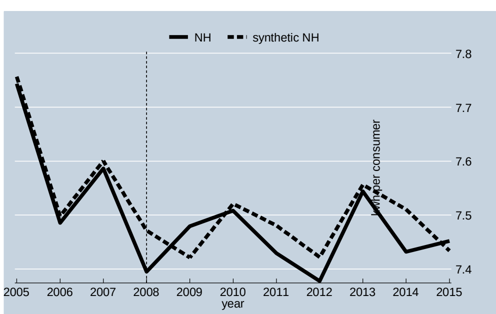
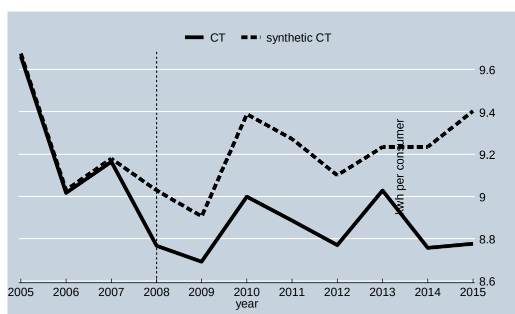



Figure 12: Residential electricity consumption in RI vs. synthetic RI

This reduction accounts for 1.34% of the average annual per consumer residential consumption of the post-treatment period. Another important finding is that electricity savings are not increasing cumulatively. The observed annual consumption is lower than the counterfactual, but its magnitude doesn't increase over time. This is an indication of an existing rebound effect. As the service of electricity decreases, consumers adjust their consumption to a higher level.

4.2.2.1 Inference about the effect of the LCP in RI  To evaluate the statistical significance of our estimates, we pose the question of whether the results could be driven entirely by chance. How often would we obtain results of this magnitude if we had randomly chosen a state, for the study, instead of Rhode Island? To answer this question, we use placebo tests. We evaluate findings and results from a  treated unit. A placebo study evaluates northeast states with moderate expenditures in EE programs. If the treatment effect was not random, the effect should be more visible in the treated state.



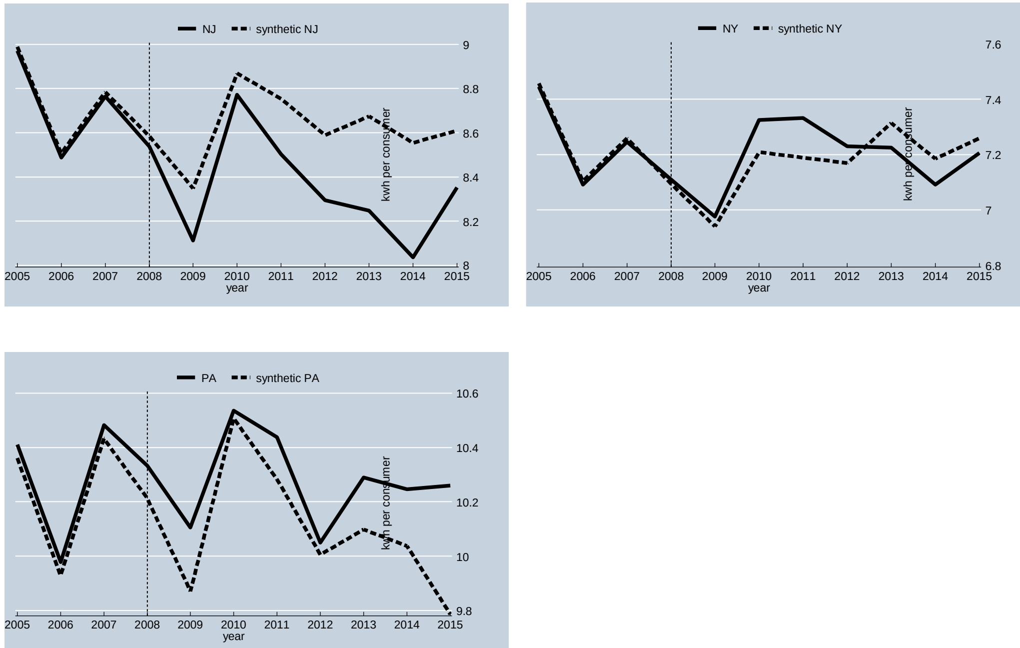



Figure 13: Residential electricity consumption – Placebo study

Figure 13: Residential electricity consumption – Placebo study demonstrates the synthetic control method to study the effects of EE programs in the Northeast US with moderate incentive programs in EE, during the same period. Moderate EE programs are defined, in this study, based on the reported savings as a percentage of the total residential consumption. Five states NH, CT, NJ, NY and PA reported less than half the percentage of electricity savings compared to RI's EE program.

Findings show that Connecticut and New Jersey have real-synthetic gaps; with their real consumption being lower than their synthetic. In contrast, Pennsylvania has the opposite effect of real-synthetic gaps. In New York and New Hampshire, the gaps are small and fluctuate in the post-intervention period.

In conclusion, the state of RI's post-intervention electricity consumption trajectory has similarities with the five states it was compared with. The treatment effect, the gap between real vs. synthetic, is more visible in the treated state (RI) compared to NY, NH, and PA. However, CT and NJ both provide large intervention effects, even without aggressive EE programs.

4.3 Cost Comparison - Energy efficiency and renewable energy generation

Over the examined period, renewable energy generation declined significantly in the US. Wind remains the most cost-effective renewable technology, and the LCOE of wind supply is close to \$0.05 per kWh. The utility-scale of solar photovoltaic technology demonstrates a higher rate of cost decrease with an average LCOE of \$0.06 per kWh. These estimates for the LCOE of renewable resources are before any incentives.

Using EE investments to decrease the demand of electricity, the claimed energy savings had a cost of \$0.069 per kWh (Hoffman, 2015). This estimate is rather conservative based on the analysis of this research. However, the comparison of the levelized cost of energy vs. energy efficiency does not consider the environmental costs of energy supply. Comparing this cost to the average cost of electricity, in the same period, \$0.1043 per kWh - Table 12- suggests that the cost of implementing EE is considerably lower than the cost of electricity supply. This finding supports the continued increase of EE program development. However, this research finds that the levelized cost of EE is higher than believed. Although the increased cost is still rather low, compared to the average cost of consumed electricity, there is a question about the cost-effectiveness of EE in comparison to renewable energy generation. The levelized cost of renewable energy has dropped drastically over the past few years and continues to decrease. As this trend continues, renewable energy programs may challenge the cost-effectiveness of EE investments. Future empirical research is needed to address an important question: “what is the tipping point where the energy markets must prioritize incentives for renewable energy programs over energy efficiency?"

## Chapter 5. Conclusion, Discussion

Energy efficiency programs provide well-documented benefits to end-users. Having a long history of implementation, the residential, commercial and industrial sectors utilize EE programs to replace inefficient legacy equipment, save energy and decrease operational costs. Since their introduction in the 1970's, and throughout their history, EE programs have not always had the same objectives. Following the 1973 energy crisis, energy independence became the top priority of national energy policies and EE programs were implemented to serve this objective. Since then, many parameters have changed in the energy sector. The market economy dominates global trade, fossil fuel reserves are higher than previously believed, (Table 25: Proved Reserves of Fossil Fuels) and new technologies, especially from renewable resources, generate cost-effective clean energy. At the same time, environmental concerns of the impact fossil fuel emissions have on climate change are at the center of every discussion regarding the future of energy generation. Although, as described, the economic environment has changed significantly, energy efficiency continues to play an important role in many states' energy policies.

In recent years, energy efficiency programs have protected end-users from the increase of energy costs. Utilities have developed customer-funded programs that provide financial incentives to ratepayers willing to invest in efficient equipment. These programs have become very popular. So much so, that spending for electricity-reducing measures increased every year for the 11-year period examined in this study. The support for these programs is almost universal amongst stakeholders. Utilities, state governments, and consumers alike, view efficiency programs positively. Utilities benefit twofold as EE programs benefit both their budgets and their profits. As shown in the analysis, administrative and other costs (not incentives to customers) represent, on average, 45% of the total expenses for the examined period. Additionally, utilities get financial benefits when they achieve their energy-saving targets. State governments benefit too, as EE programs provide funding for state energy programs. Moreover, EE incentives are in-line with consumer's increasingly environmentally conscious behavior. Consumers, especially residential, are supportive because EE's popular rebates make the purchase of high-end, efficient equipment more affordable. Concerns that EE programs tend to benefit wealthier consumers, and increase the cost of electricity supply, are not prevalent.

It is not in the scope of this study to question the benefits from energy efficiency improvements or examine who benefits most from EE programs. This study examines the effectiveness of these programs and their magnitude, as reported by utilities. The first empirical application, at the national level, provides evidence that the cost-effectiveness of these programs is lower than utilities claim. The results imply a price elasticity of energy efficiency ranging between 0.29 and 0.54. These numbers indicate a rebound effect. Consequently, energy savings are less than proportional to the increase in energy efficiency. However, consumers also benefit from an increase in energy services, since they get more of the service, at less cost to them.

This research makes the claim that energy consumption can be better explained by using the principles of economic behavior, as opposed to the reasoning-by-analogy approach. Economic agents, consumers, and businesses adjust their demand for energy by increasing their consumption as the cost of energy drops. Doing so, increases their utility. This behavior is not taken into account by the engineering reports utilities produce. Utilities evaluate energy savings using the reasoning-by-analogy approach; estimating an equipment's efficiency and then scaling up the benefits to society. However, this analogical reasoning is based on the assumption that the price elasticity of demand is very small (or even zero) for all consumers, which is a very strong assumption. As the cost for the service provided from energy usage decreases, the consumption of the service will increase by the commodity's elasticity. As a result, the rebound effect will partially offset increases in energy efficiency. So, reductions in demand decrease are less than in proportion to increase in energy efficiency. However, it is important to recognize that there are significant welfare implications from such behavior. Consumers benefit from receiving more of the service. Further research is needed to quantify the exact welfare implications, but it can be assumed that utility increases when one can use more electricity. A good example of this, are the EE investments in highway lighting that have decreased energy and maintenance costs. Due to the reduction in costs of lighting highways, the RIDOT chose to significantly increase the hours highway lights are on. In this case, use of electricity was reduced less than in proportion to the increase in energy efficiency. Ultimately, less electricity was used, and citizens also benefit from safer highway conditions, due to increased highway lighting.

The state-level empirical application provided an insight into expectations from aggressive EE programs. For a number of years, Rhode Island has been the state with the highest per capita expenditure for EE programs, in the nation. Following a comparative analysis, there are indications that Rhode Island does indeed realize savings but those savings are lower than expected.

In the examined period, 2005 - 2015, the state-level empirical application assessed the energy efficiency policy of Rhode Island and compared its outcome to Maine and New Hampshire. Findings of the difference in differences analysis provide evidence that the higher savings observed in RI, compared to the control states of NH and ME, are not statistically significant. However, a re-evaluation of the Rhode Island EE policy, using the synthetic control method identifies that by the year 2015, annual per-consumer residential electricity consumption in Rhode Island was 97 kWh (1.34%) lower, on average, than it would have been in the absence of this policy.

There are numerous reasons for this. The cost per energy unit saved is a result of many parameters; from how a state's program is developed to how effectively a program is implemented. States with a long history in EE, like New York and California, have decreased their rate of spending on such programs, in recent years. Both these states have increased their efforts in other areas such as adoption of higher standards for appliances and equipment, adopting building codes that make homes more efficient, and emphasizing improvements in transportation. Moving forward it is important for states to reevaluate the priorities of their EE programs. Financial incentives have limitations and the cost of EE, per energy unit saved (kWh), is already at the same level as the levelized cost of renewable energy generation. Of course, it is important to keep in mind that renewable energy has negative externalities as well. Renewable energy impacts wildlife (especially birds), and has noise and visual impacts, that are not embodied in the LCOE. In comparison, EE has mostly positive externalities. This is an important environmental advantage of the EE energy policies. As consumers increase their investments in renewable energy, they become more sensitive to energy issues, in general. Investments in renewable energy may lead to larger changes in demand patterns than the investments in EE programs have been able to accomplish. Further research is needed to examine how investments in renewable energy affect energy efficiency.

There is no doubt that incentive programs in energy efficiency have merits, both conceptually and practically. However, there are likely to be diminishing returns to investments in energy efficiency. Further study is needed to find the proper balance between investments in energy production and demand management, through energy efficiency programs.

## Figures and Tables

Table 7: Annual Costs of Electricity Efficiency Program Implementation

| Year | EE Total Cost (,000) | EE Incentives (,000)(*) | Percentage over total | Other Costs (,000)(**) | Percentage over total |
|---|---|---|---|---|---|
| 2005 | $1,258,894 | $634,867 | 50% | $624,027 | 50% |
| 2006 | $1,348,756 | $650,607 | 48% | $698,148 | 52% |
| 2007 | $1,787,603 | $845,536 | 47% | $942,067 | 53% |
| 2008 | $2,470,412 | $1,079,891 | 44% | $1,390,521 | 56% |
| 2009 | $2,528,808 | $1,133,910 | 45% | $1,394,898 | 55% |
| 2010 | $3,097,294 | $1,614,853 | 52% | $1,482,441 | 48% |
| 2011 | $4,254,096 | $2,369,344 | 56% | $1,884,752 | 44% |
| 2012 | $4,644,657 | $2,454,144 | 53% | $2,190,513 | 47% |
| 2013 | $4,819,062 | $2,872,906 | 60% | $1,946,156 | 40% |
| 2014 | $5,620,182 | $3,411,034 | 61% | $2,209,148 | 39% |
| 2015 | $5,730,573 | $3,449,385 | 60% | $2,281,188 | 40% |
| **Total** | **$37,560,337** | **$20,516,477** | **55%** | **$17,043,859** | **45%** |

(*) Energy Efficiency (EE) Customer incentives are the total financial value provided to a customer for program participation: cash payments, or lowered tariff rates relative to non-participants, in-kind services (e.g., design services), or other benefits directly provided to the customer for their program participation.

(**) Other costs: Includes direct and indirect costs for the utility. Direct Costs, excluding incentive payments: The cost for implementing energy efficiency programs (in thousand dollars) incurred by the utility. Indirect Cost: A utility cost that may not be meaningfully identified with any particular EE program category. Indirect costs could be attributable to one of several accounting cost categories (i.e., Administrative, Marketing, Monitoring & Evaluation, Utility-Earned Incentives, Other).

Table 8: Reported electricity savings and associated costs from EE Programs (2005-2015)

| Year | Energy savings (*) (MWh) | Program Total Cost $( ,000) |
|---|---|---|
| 2005 | 5,878,693 | 1,258,894 |
| 2006 | 5,393,631 | 1,348,756 |
| 2007 | 7,679,812 | 1,787,603 |
| 2008 | 10,433,487 | 2,470,412 |
| 2009 | 12,906,637 | 2,528,808 |
| 2010 | 13,518,154 | 3,097,294 |
| 2011 | 21,421,322 | 4,254,096 |
| 2012 | 21,478,470 | 4,644,657 |
| 2013 | 24,681,728 | 4,819,062 |
| 2014 | 26,465,220 | 5,620,182 |
| 2015 | 26,189,500 | 5,730,573 |

Note: Incremental annual savings summarize the expected effect in demand in terms of MWh for each utility caused by new participants in existing programs and all participants in new programs during a given year.

Table 9: Annual Electricity Consumption in US

| Year | Sales (*) | Revenues (*) | Customers | Utilities |
|---|---|---|---|---|
| 2005 | 3,684,351,232 | $ 301,982,208 | 139,922,272 | 3,541 |
| 2006 | 3,693,140,992 | $ 330,727,680 | 141,966,848 | 3,554 |
| 2007 | 3,787,363,072 | $ 348,160,512 | 143,681,184 | 3,565 |
| 2008 | 3,733,964,544 | $ 363,583,104 | 143,395,760 | 3,635 |
| 2009 | 3,596,795,136 | $ 353,289,248 | 143,529,312 | 3,675 |
| 2010 | 3,754,841,344 | $ 368,918,144 | 144,140,256 | 3,683 |
| 2011 | 3,749,846,272 | $ 371,049,088 | 144,509,152 | 3,745 |
| 2012 | 3,694,649,856 | $ 363,687,488 | 145,293,840 | 2,776 |
| 2013 | 3,724,867,840 | $ 375,057,728 | 146,288,576 | 2,800 |
| 2014 | 3,764,700,160 | $ 393,096,416 | 147,373,696 | 3,038 |
| 2015 | 3,758,992,384 | $ 391,341,472 | 148,633,024 | 3,212 |

Note: (*) Sales are reported in MWh and revenues in $(, 000). Includes residential, commercial, industrial and transportation sector. Numbers represent all utilities in US - included utilities that didn't implement DSM programs.

Table 10: Electricity consumption by Sector in US (MWh)

| Year | Residential | Commercial | Industrial | Transportation |
|---|---|---|---|---|
| 2005 | 1,367,509,248 | 1,285,521,664 | 1,023,814,080 | 7,506,321 |
| 2006 | 1,359,551,360 | 1,310,322,560 | 1,015,909,568 | 7,357,543 |
| 2007 | 1,400,106,112 | 1,346,912,000 | 1,032,172,352 | 8,172,595 |
| 2008 | 1,380,661,760 | 1,336,133,504 | 1,009,516,160 | 7,653,211 |
| 2009 | 1,364,758,144 | 1,306,852,480 | 917,416,448 | 7,767,989 |
| 2010 | 1,445,708,416 | 1,330,199,424 | 971,221,184 | 7,712,412 |
| 2011 | 1,422,801,152 | 1,328,057,472 | 991,315,584 | 7,672,084 |
| 2012 | 1,374,514,688 | 1,327,101,184 | 985,713,856 | 7,320,028 |
| 2013 | 1,394,812,160 | 1,337,078,784 | 985,351,872 | 7,625,041 |
| 2014 | 1,407,208,320 | 1,352,158,208 | 997,576,128 | 7,757,555 |
| 2015 | 1,404,096,512 | 1,360,751,488 | 986,507,712 | 7,636,632 |

Note: (*) Electricity consumption is reported in MWh. Numbers represent all utilities in US - included utilities that didn't implement DSM programs.

Table 11: Share of Electricity Demand by Sector

| Year | Residential | Commercial | Industrial | Transportation |
|---|---|---|---|---|
| 2005 | 37.12% | 34.89% | 27.79% | 0.20% |
| 2006 | 36.81% | 35.48% | 27.51% | 0.20% |
| 2007 | 36.97% | 35.56% | 27.25% | 0.22% |
| 2008 | 36.98% | 35.78% | 27.04% | 0.20% |
| 2009 | 37.94% | 36.33% | 25.51% | 0.22% |
| 2010 | 38.50% | 35.43% | 25.87% | 0.21% |
| 2011 | 37.94% | 35.42% | 26.44% | 0.20% |
| 2012 | 37.20% | 35.92% | 26.68% | 0.20% |
| 2013 | 37.45% | 35.90% | 26.45% | 0.20% |
| 2014 | 37.38% | 35.92% | 26.50% | 0.21% |
| 2015 | 37.35% | 36.20% | 26.24% | 0.20% |

Note: (*) Shares of electricity demand represents all utilities (US) - included utilities that didn't implement DSM programs.

Table 12: Average Price of Electricity to Ultimate Customers - Total by End-Use Sector, 2005 - 2015 (Cents per Kilowatt-hour)

| *Period* | Residential | Commercial | Industrial | Transportation | All Sectors | CPI Average | Adjusted (base:2015) |
|---|---|---|---|---|---|---|---|
| 2005 | 9.45 | 8.67 | 5.73 | 8.57 | 8.14 | 195.3 | 9.88 |
| 2006 | 10.40 | 9.46 | 6.16 | 9.54 | 8.90 | 201.6 | 10.46 |
| 2007 | 10.65 | 9.65 | 6.39 | 9.70 | 9.13 | 207.3 | 10.44 |
| 2008 | 11.26 | 10.26 | 6.96 | 10.71 | 9.74 | 215.3 | 10.72 |
| 2009 | 11.51 | 10.16 | 6.83 | 10.66 | 9.82 | 214.5 | 10.85 |
| 2010 | 11.54 | 10.19 | 6.77 | 10.56 | 9.83 | 218.1 | 10.68 |
| 2011 | 11.72 | 10.24 | 6.82 | 10.46 | 9.90 | 224.9 | 10.43 |
| 2012 | 11.88 | 10.09 | 6.67 | 10.21 | 9.84 | 229.6 | 10.16 |
| 2013 | 12.13 | 10.26 | 6.89 | 10.55 | 10.07 | 233 | 10.24 |
| 2014 | 12.52 | 10.74 | 7.10 | 10.45 | 10.44 | 236.7 | 10.45 |
| 2015 | 12.65 | 10.64 | 6.91 | 10.09 | 10.41 | 237 | 10.41 |
| | | | | | | average | **10.43** |

Note: Geographic coverage is the 50 States and the District of Columbia.

Sources: U.S. Energy Information Administration, Form EIA-826, Monthly Electric Sales and Revenue Report with State Distributions Report; Form EIA-861, Annual Electric Power Industry Report; and Form EIA-861S, Annual Electric Power Industry Report (Short Form).

Table 13: Cooling and Heating Degree Days (CDD-HDD) in Contiguous US

| Year | CDD | HDD | Observations |
|---|---|---|---|
| 2005 | 55,804 | 249,316 | 576 |
| 2006 | 54,149 | 232,922 | 576 |
| 2007 | 56,846 | 247,366 | 576 |
| 2008 | 49,304 | 262,532 | 576 |
| 2009 | 46,509 | 261,481 | 576 |
| 2010 | 59,385 | 255,095 | 576 |
| 2011 | 57,873 | 251,566 | 576 |
| 2012 | 60,116 | 220,438 | 576 |
| 2013 | 50,688 | 262,792 | 576 |
| 2014 | 48,634 | 266,883 | 576 |
| 2015 | 56,618 | 239,392 | 576 |

HDD and CDD are defined to a base temperature of 65° F which is adequate for human comfort. The degree days are the number of degrees of Fahrenheit that mean outside air temperature deviates from the base (65° F) temperature.
Monthly observations were obtained from National Oceanic and Atmospheric Administration (NOAA)

Table 14: Mean Annual Heating Degree Days by State (2005-2015)

| | State | HDD | | State | HDD |
|---|---|---|---|---|---|
| **1** | North Dakota | 9,146 | **25** | Oregon | 5,298 |
| **2** | Montana | 8,463 | **26** | New Jersey | 5,146 |
| **3** | Minnesota | 8,458 | **27** | West Virginia | 5,089 |
| **4** | Wyoming | 8,185 | **28** | Missouri | 4,975 |
| **5** | Vermont | 7,904 | **29** | Kansas | 4,831 |
| **6** | Maine | 7,735 | **30** | Maryland | 4,578 |
| **7** | South Dakota | 7,573 | **31** | Delaware | 4,493 |
| **8** | Wisconsin | 7,483 | **32** | New Mexico | 4,477 |
| **9** | New Hampshire | 7,434 | **33** | Kentucky | 4,421 |
| **10** | Colorado | 7,043 | **34** | Virginia | 4,268 |
| **11** | Utah | 7,003 | **35** | Tennessee | 3,786 |
| **12** | Idaho | 6,893 | **36** | Oklahoma | 3,543 |
| **13** | Iowa | 6,785 | **37** | Nevada | 3,469 |
| **14** | Michigan | 6,726 | **38** | North Carolina | 3,392 |
| **15** | Nebraska | 6,232 | **39** | Arkansas | 3,386 |
| **16** | Massachusetts | 6,133 | **40** | Georgia | 2,837 |
| **17** | Illinois | 6,089 | **41** | California | 2,811 |
| **18** | New York | 6,005 | **42** | Alabama | 2,718 |
| **19** | Connecticut | 5,867 | **43** | South Carolina | 2,631 |
| **20** | Rhode Island | 5,764 | **44** | Mississippi | 2,443 |
| **21** | Ohio | 5,720 | **45** | Arizona | 1,950 |
| **22** | Pennsylvania | 5,713 | **46** | Texas | 1,845 |
| **23** | Washington | 5,664 | **47** | Louisiana | 1,709 |
| **24** | Indiana | 5,646 | **48** | Florida | 681 |

Note: The degree days are the number of degrees of Fahrenheit that mean outside air temperature deviates from the base (65° F) temperature. The higher the amount of heating degree days is, the higher the amount of energy is needed to heat a building.

Source: National Oceanic and Atmospheric Administration (NOAA).

Table 15: Mean Annual Cooling Degree Days by State (2005-2015)

| | State | CDD | | State | CDD |
|---|---|---|---|---|---|
| **1** | Florida | 3,541 | **25** | New Jersey | 873 |
| **2** | Arizona | 3,077 | **26** | Iowa | 818 |
| **3** | Texas | 2,839 | **27** | West Virginia | 791 |
| **4** | Louisiana | 2,700 | **28** | Ohio | 780 |
| **5** | Nevada | 2,204 | **29** | South Dakota | 717 |
| **6** | Mississippi | 2,189 | **30** | Pennsylvania | 700 |
| **7** | Oklahoma | 1,964 | **31** | New York | 618 |
| **8** | Alabama | 1,954 | **32** | Connecticut | 600 |
| **9** | South Carolina | 1,944 | **33** | Michigan | 577 |
| **10** | Arkansas | 1,809 | **34** | Rhode Island | 563 |
| **11** | Georgia | 1,736 | **35** | Utah | 547 |
| **12** | Kansas | 1,507 | **36** | Wisconsin | 521 |
| **13** | North Carolina | 1,466 | **37** | Massachusetts | 515 |
| **14** | Tennessee | 1,425 | **38** | Idaho | 514 |
| **15** | Missouri | 1,283 | **39** | Minnesota | 475 |
| **16** | Kentucky | 1,228 | **40** | North Dakota | 455 |
| **17** | Delaware | 1,157 | **41** | Colorado | 355 |
| **18** | Maryland | 1,143 | **42** | Wyoming | 303 |
| **19** | Virginia | 1,125 | **43** | New Hampshire | 299 |
| **20** | Nebraska | 1,025 | **44** | Oregon | 235 |
| **21** | New Mexico | 1,020 | **45** | Vermont | 235 |
| **22** | California | 939 | **46** | Maine | 233 |
| **23** | Indiana | 910 | **47** | Montana | 222 |
| **24** | Illinois | 892 | **48** | Washington | 187 |

Note: The degree days are the number of degrees of Fahrenheit that mean outside air temperature deviates from the base (65° F) temperature. The higher the amount of cooling degree days is, the higher the amount of energy is needed to cool a building.

Source: National Oceanic and Atmospheric Administration (NOAA).

Table 16: Residential Annual Electricity Consumption by State (2014)

| | Per Capita | Sales (MWh) | Counts | Per Customer | Ratio |
|---|---|---|---|---|---|
| Alaska | 2,773 | 2,043,614 | 281,438 | 7,261 | 2.62 |
| Alabama | 6,795 | 32,929,598 | 2,169,790 | 15,176 | 2.23 |
| Arkansas | 6,215 | 18,441,120 | 1,345,009 | 13,711 | 2.21 |
| Arizona | 4,807 | 32,346,080 | 2,661,694 | 12,152 | 2.53 |
| California | 2,304 | 89,360,680 | 13,256,068 | 6,741 | 2.93 |
| Colorado | 3,378 | 18,092,932 | 2,193,520 | 8,248 | 2.44 |
| Connecticut | 3,554 | 12,777,579 | 1,459,239 | 8,756 | 2.46 |
| Delaware | 4,963 | 4,644,841 | 407,508 | 11,398 | 2.30 |
| Florida | 5,854 | 116,535,264 | 8,891,020 | 13,107 | 2.24 |
| Georgia | 5,662 | 57,167,388 | 4,137,057 | 13,818 | 2.44 |
| Hawaii | 1,820 | 2,583,770 | 425,168 | 6,077 | 3.34 |
| Iowa | 4,640 | 14,426,582 | 1,348,641 | 10,697 | 2.31 |
| Idaho | 4,976 | 8,134,913 | 690,277 | 11,785 | 2.37 |
| Illinois | 3,572 | 46,009,456 | 5,145,022 | 8,943 | 2.50 |
| Indiana | 5,108 | 33,703,964 | 2,784,660 | 12,103 | 2.37 |
| Kansas | 4,714 | 13,684,952 | 1,228,858 | 11,136 | 2.36 |
| Kentucky | 6,209 | 27,399,768 | 1,939,489 | 14,127 | 2.28 |
| Louisiana | 6,754 | 31,400,684 | 2,026,223 | 15,497 | 2.29 |
| Massachusetts | 2,971 | 20,071,160 | 2,720,128 | 7,379 | 2.48 |
| Maryland | 4,601 | 27,487,632 | 2,234,962 | 12,299 | 2.67 |
| Maine | 3,505 | 4,660,605 | 706,952 | 6,593 | 1.88 |
| Michigan | 3,380 | 33,514,992 | 4,273,126 | 7,843 | 2.32 |
| Minnesota | 4,176 | 22,791,466 | 2,345,860 | 9,716 | 2.33 |
| Missouri | 5,903 | 35,792,644 | 2,724,541 | 13,137 | 2.23 |
| Mississippi | 6,322 | 18,922,096 | 1,263,583 | 14,975 | 2.37 |
| Montana | 4,857 | 4,969,243 | 485,041 | 10,245 | 2.11 |
| North Carolina | 5,900 | 58,649,992 | 4,303,476 | 13,629 | 2.31 |
| North Dakota | 7,241 | 5,357,514 | 360,171 | 14,875 | 2.05 |
| Nebraska | 5,326 | 10,028,238 | 817,425 | 12,268 | 2.30 |
| New Hampshire | 3,396 | 4,510,487 | 606,883 | 7,432 | 2.19 |
| New Jersey | 3,120 | 27,892,582 | 3,470,874 | 8,036 | 2.58 |
| New Mexico | 3,170 | 6,611,970 | 869,875 | 7,601 | 2.40 |
| Nevada | 4,199 | 11,916,521 | 1,110,535 | 10,730 | 2.56 |
| New York | 2,531 | 49,974,912 | 7,046,829 | 7,092 | 2.80 |
| Ohio | 4,553 | 52,804,336 | 4,882,159 | 10,816 | 2.38 |
| Oklahoma | 6,018 | 23,351,144 | 1,710,352 | 13,653 | 2.27 |
| Oregon | 4,688 | 18,617,612 | 1,669,124 | 11,154 | 2.38 |
| Pennsylvania | 4,236 | 54,195,336 | 5,289,211 | 10,246 | 2.42 |
| Rhode Island | 2,910 | 3,070,347 | 438,879 | 6,996 | 2.40 |
| South Carolina | 6,361 | 30,715,986 | 2,157,091 | 14,240 | 2.24 |
| South Dakota | 5,659 | 4,827,368 | 384,749 | 12,547 | 2.22 |
| Tennessee | 6,496 | 42,538,248 | 2,756,932 | 15,430 | 2.38 |
| Texas | 5,223 | 140,899,744 | 10,138,874 | 13,897 | 2.66 |
| United States | 4,413 | 1,407,208,312 | 128,680,416 | 10,936 | 2.48 |
| Utah | 3,045 | 8,963,971 | 1,000,416 | 8,960 | 2.94 |
| Virginia | 5,577 | 46,443,716 | 3,303,676 | 14,058 | 2.52 |
| Vermont | 3,383 | 2,121,347 | 310,932 | 6,823 | 2.02 |
| Washington | 4,967 | 35,082,960 | 2,907,705 | 12,066 | 2.43 |
| Wisconsin | 3,807 | 21,925,712 | 2,631,430 | 8,332 | 2.19 |
| West Virginia | 6,485 | 11,990,728 | 862,869 | 13,896 | 2.14 |
| Wyoming | 4,712 | 2,752,313 | 265,720 | 10,358 | 2.20 |

Note: Ratio=consumption per customer (meter) / consumption per capita
Highlighted cells indicate the 5 lowest values in each column.
Source: Author / Raw data: Energy Information Administration, State Energy Data System

Table 17: Annual Per Capita Electricity Consumption

| | 1990 | 2000 | 2010 | 2015 | Delta I | Delta II |
|---|---|---|---|---|---|---|
| Alaska | 3,004 | 2,954 | 2,931 | 2,773 | (230) | (158) |
| Alabama | 5,116 | 6,459 | 7,425 | 6,795 | 1,679 | (630) |
| Arkansas | 4,479 | 5,551 | 6,581 | 6,215 | 1,736 | (366) |
| Arizona | 4,174 | 4,814 | 5,064 | 4,807 | 633 | (257) |
| California | 2,222 | 2,331 | 2,337 | 2,304 | 81 | (34) |
| Colorado | 2,959 | 3,242 | 3,586 | 3,378 | 419 | (208) |
| Connecticut | 3,152 | 3,413 | 3,649 | 3,554 | 402 | (95) |
| District of Columbia | 2,446 | 2,839 | 3,509 | 3,139 | 693 | (370) |
| Delaware | 3,957 | 4,548 | 5,289 | 4,963 | 1,006 | (326) |
| Florida | 5,457 | 6,169 | 6,485 | 5,854 | 398 | (631) |
| Georgia | 4,596 | 5,416 | 6,337 | 5,662 | 1,066 | (675) |
| Hawaii | 2,088 | 2,278 | 2,191 | 1,820 | (268) | (372) |
| Iowa | 3,780 | 4,107 | 4,771 | 4,640 | 860 | (130) |
| Idaho | 5,559 | 5,393 | 5,180 | 4,976 | (584) | (204) |
| Illinois | 2,870 | 3,229 | 3,783 | 3,572 | 701 | (212) |
| Indiana | 3,978 | 4,703 | 5,401 | 5,108 | 1,130 | (293) |
| Kansas | 3,835 | 4,650 | 5,014 | 4,714 | 879 | (300) |
| Kentucky | 4,552 | 5,773 | 6,701 | 6,209 | 1,657 | (492) |
| Louisiana | 5,077 | 6,198 | 7,190 | 6,754 | 1,678 | (436) |
| Massachusetts | 2,587 | 2,761 | 3,261 | 2,971 | 384 | (290) |
| Maryland | 3,980 | 4,509 | 4,999 | 4,601 | 621 | (398) |
| Maine | 3,192 | 2,926 | 3,292 | 3,505 | 313 | 212 |
| Michigan | 2,719 | 3,086 | 3,511 | 3,380 | 661 | (131) |
| Minnesota | 3,385 | 3,776 | 4,230 | 4,176 | 792 | (53) |
| Missouri | 4,221 | 5,276 | 6,221 | 5,903 | 1,681 | (319) |
| Mississippi | 4,756 | 6,037 | 6,793 | 6,322 | 1,566 | (471) |
| Montana | 4,198 | 4,323 | 4,786 | 4,857 | 660 | 71 |
| North Carolina | 4,974 | 5,758 | 6,503 | 5,900 | 927 | (602) |
| North Dakota | 4,630 | 5,280 | 6,508 | 7,241 | 2,610 | 732 |
| Nebraska | 4,298 | 4,869 | 5,523 | 5,326 | 1,027 | (197) |
| New Hampshire | 3,097 | 2,948 | 3,405 | 3,396 | 299 | (9) |
| New Jersey | 2,640 | 2,912 | 3,442 | 3,120 | 480 | (322) |
| New Mexico | 2,343 | 2,711 | 3,270 | 3,170 | 827 | (100) |
| Nevada | 4,537 | 4,659 | 4,297 | 4,199 | (338) | (98) |
| New York | 2,141 | 2,264 | 2,626 | 2,531 | 390 | (95) |
| Ohio | 3,488 | 4,091 | 4,720 | 4,553 | 1,066 | (167) |
| Oklahoma | 5,423 | 5,686 | 6,300 | 6,018 | 595 | (282) |
| Oregon | 5,378 | 5,310 | 4,909 | 4,688 | (689) | (220) |
| Pennsylvania | 3,206 | 3,664 | 4,347 | 4,236 | 1,030 | (111) |
| Rhode Island | 2,362 | 2,537 | 2,961 | 2,910 | 548 | (51) |
| South Carolina | 5,215 | 6,280 | 7,086 | 6,361 | 1,146 | (726) |
| South Dakota | 4,112 | 4,528 | 5,672 | 5,659 | 1,547 | (13) |
| Tennessee | 5,876 | 6,420 | 7,109 | 6,496 | 620 | (613) |
| Texas | 4,840 | 5,581 | 5,433 | 5,223 | 383 | (211) |
| United States | 3,702 | 4,226 | 4,673 | 4,413 | 711 | (261) |
| Utah | 2,453 | 2,902 | 3,183 | 3,045 | 592 | (139) |
| Virginia | 4,525 | 5,283 | 6,035 | 5,577 | 1,052 | (458) |
| Vermont | 3,202 | 3,339 | 3,399 | 3,383 | 181 | (17) |
| Washington | 5,876 | 5,589 | 5,177 | 4,967 | (909) | (210) |
| Wisconsin | 3,340 | 3,708 | 3,919 | 3,807 | 467 | (112) |
| West Virginia | 4,226 | 5,389 | 6,711 | 6,485 | 2,259 | (226) |
| Wyoming | 3,789 | 4,257 | 4,827 | 4,712 | 924 | (114) |

Note: Highlighted cells indicate the 5 lowest values in each column.
Delta I column: Difference between years (2015)-(1990)
Delta II column: Difference between years (2015)-(2000)
Source: Author / Raw data: Energy Information Administration, State Energy Data System

Table 18: Total Energy Consumed per Capita, 2015 (million Btu)

| Rank | State | Total Energy | Rank | State | Total Energy |
|---|---|---|---|---|---|
| 1 | LA | 912 | 26 | ME | 305 |
| 2 | WY | 893 | 27 | PA | 303 |
| 3 | AK | 840 | 28 | MO | 301 |
| 4 | ND | 803 | 29 | DE | 294 |
| 5 | IA | 479 | 30 | VA | 283 |
| 6 | TX | 470 | 31 | GA | 280 |
| 7 | NE | 450 | 32 | MI | 279 |
| 8 | SD | 447 | 33 | WA | 278 |
| 9 | IN | 430 | 34 | CO | 272 |
| 10 | WV | 421 | 35 | DC | 267 |
| 11 | OK | 417 | 36 | UT | 264 |
| 12 | AL | 393 | 37 | NJ | 256 |
| 13 | KY | 390 | 38 | NC | 251 |
| 14 | MS | 379 | 39 | OR | 238 |
| 14 | MT | 379 | 40 | MD | 233 |
| 16 | KS | 372 | 41 | NH | 229 |
| 17 | AR | 354 | 42 | NV | 225 |
| 18 | SC | 337 | 43 | MA | 213 |
| 19 | TN | 329 | 44 | VT | 211 |
| 20 | NM | 325 | 44 | AZ | 211 |
| 21 | MN | 323 | 46 | FL | 210 |
| 22 | OH | 322 | 46 | CT | 210 |
| 23 | ID | 317 | 48 | HI | 198 |
| 24 | WI | 308 | 49 | CA | 197 |
| 25 | IL | 307 | 50 | RI | 192 |
| | | | 51 | NY | 189 |

Note: Rankings are based on the fuel source data values.

Table 19: Effect of EE programs in Electricity Consumption

Dependent Variable: First Difference (Δ) of Electricity Consumption

| VARIABLES | (1)<br>Model1 | (2)<br>Model2 | (3)<br>Model3 | (4)<br>Model4 |
|---|---|---|---|---|
| EE Investments | -0.00778*** | -0.00627*** | -0.00576*** | -0.00509** |
| | (0.00263) | (0.00227) | (0.00221) | (0.00214) |
| Customers | 0.682*** | 0.866*** | 0.852*** | 0.824*** |
| | (0.149) | (0.127) | (0.119) | (0.118) |
| CDD | 0.000104*** | 0.000101*** | 0.000133*** | 0.000123*** |
| | (1.82e-05) | (1.55e-05) | (3.23e-05) | (3.52e-05) |
| HDD | 2.69e-05*** | 2.15e-05*** | 4.25e-05*** | 4.20e-05*** |
| | (3.04e-06) | (4.21e-06) | (1.09e-05) | (1.07e-05) |
| lnNGEID | | 0.0243* | 0.0121 | 0.0273 |
| | | (0.0127) | (0.0101) | (0.0221) |
| lnGDPRV | | -0.109** | -0.190*** | 0.166 |
| | | (0.0511) | (0.0629) | (0.152) |
| lnESRCD | | 0.110 | -0.237* | -0.137 |
| | | (0.0714) | (0.141) | (0.144) |
| SHRCOM | | | 3.067** | 2.881** |
| | | | (1.357) | (1.406) |
| SHRIND | | | 2.790** | 2.668* |
| | | | (1.370) | (1.421) |
| ESACDdata | | | -0.000472 | -0.000368 |
| | | | (0.00114) | (0.00116) |
| ESCCDdata | | | 0.00409 | 0.00759 |
| | | | (0.00516) | (0.00616) |
| ESICDdata | | | 0.00878** | 0.00463 |
| | | | (0.00375) | (0.00431) |
| Constant | 6.315*** | 5.393*** | 5.492*** | 1.049 |
| | (1.536) | (1.231) | (1.231) | (1.818) |
| R-squared | 0.325 | 0.410 | 0.440 | 0.447 |
| Number of unique_id | 734 | 734 | 734 | 734 |
| Year FE | No | No | No | Yes |
| Est. cost/kWh | $0.050 | $0.056 | $0.058 | $0.061 |
| Adjusted | $0.053 | $0.060 | $0.062 | $0.065 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Difference in differences estimate of the EE program spending

Residential electricity consumption (period 2005-2015).

**Dependent variable**: Residential electricity consumption (ln)

| Variables | (1) Random Effect | (2) Population Averaged Model | (3) Fixed Effect | (4) Fixed Effect |
|---|---|---|---|---|
| Utilities (relative to NH - ME) | | | | |
| RI | -0.222 | -0.217 | | |
| | (0.216) | (0.187) | | |
| Time period (relative to Post Implementation) | | | | |
| T1 | -0.084 | -0.061 | -0.103 | 0.328 |
| | (0.109) | (0.104) | (0.188) | (0.452) |
| T2 | -0.081 | -0.051 | -0.100 | -0.159 |
| | (0.108) | (0.115) | (0.172) | (0.521) |
| Difference-in-differences | | | | |
| RI-T1 | -0.028 | 0.020 | -0.057 | -0.026 |
| | (0.067) | (0.052) | (0.095) | (0.137) |
| RI-T2 | 0.051 | 0.049 | 0.042 | 0.104 |
| | (0.089) | (0.109) | (0.116) | (0.189) |
| Consumers (n) | 1.060*** | 1.045*** | 1.080*** | 1.079*** |
| | (0.037) | (0.0281) | (0.0618) | (0.0581) |
| CDD | -0.000855* | -0.000975* | -0.000783* | -0.00105 |
| | (0.000491) | (0.000525) | (0.000462) | (0.00106) |
| HDD | -0.000176 | -0.000174 | -0.000182* | 0.000208 |
| | (0.000109) | (0.000113) | (0.000109) | (0.000321) |
| Electricity cost | -0.602 | -0.886 | -0.465 | -0.845 |
| | (0.545) | (0.556) | (0.776) | (1.294) |
| Income | 0.412 | 0.805 | -0.191 | 0.181 |
| | (0.724) | (0.594) | (3.401) | (5.122) |
| Occupancy | 28.96* | 33.10* | 27.61 | 38.63 |
| | (16.33) | (17.05) | (19.33) | (34.03) |
| Constant | 3.559 | 3.258 | 5.156 | 2.358 |
| | (3.038) | (3.006) | (10.79) | (18.41) |
| Observations | 326 | 326 | 326 | 326 |
| R-squared | | | 0.867 | 0.871 |
| Number of Utilities | 71 | 71 | 71 | 71 |
| Utility FE | | | YES | YES |
| Year FE | | | | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 14: Annual Residential Electricity Consumption (2015)

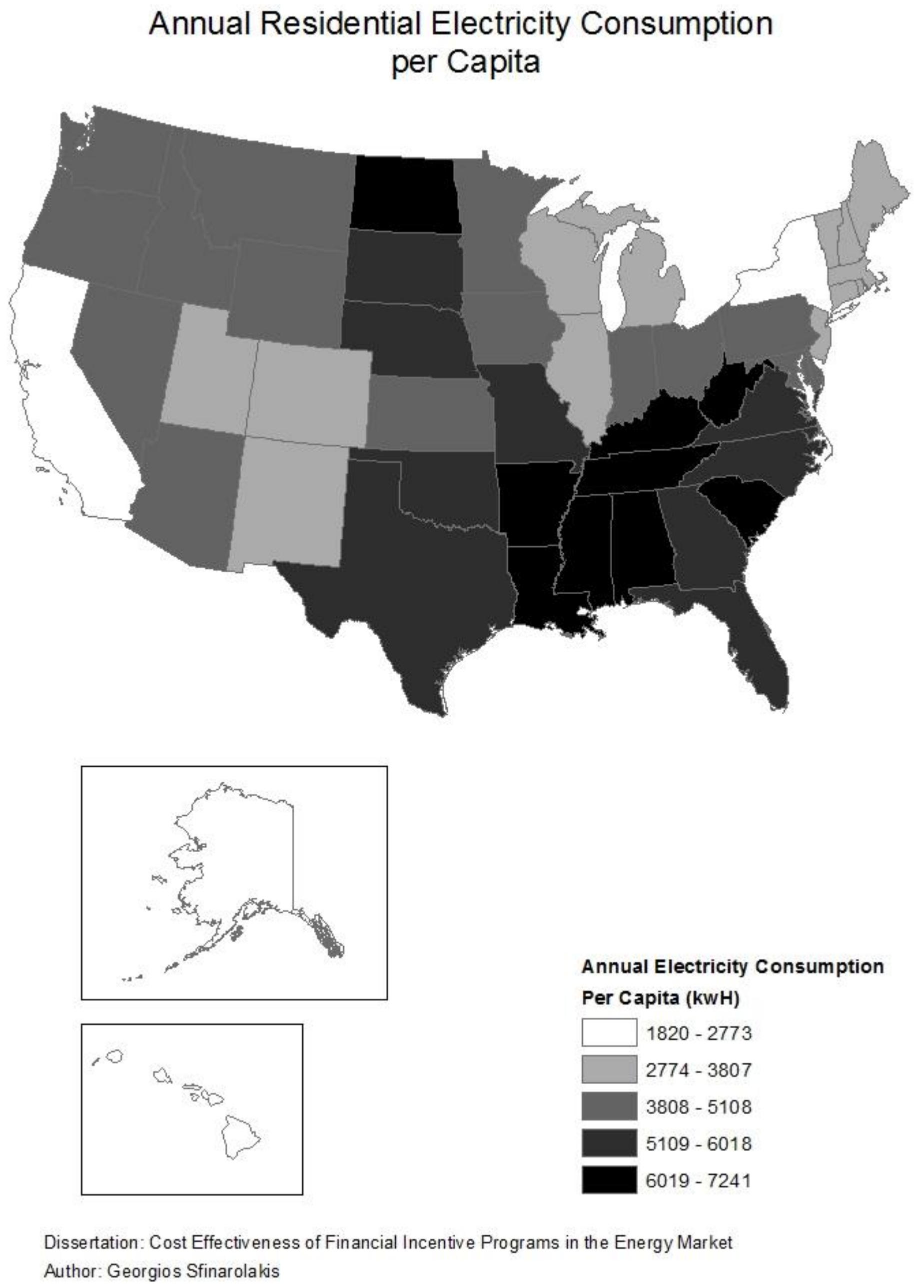
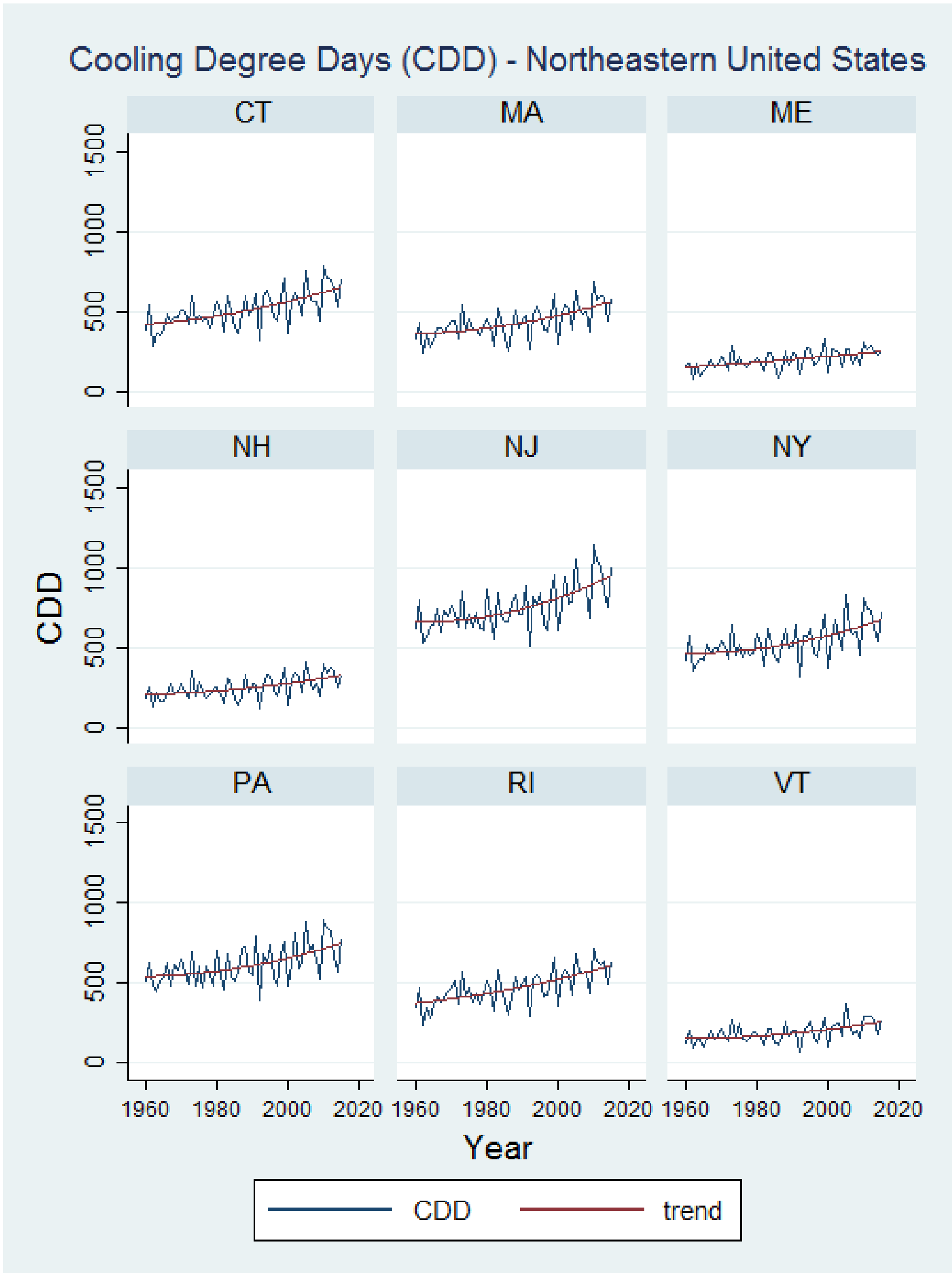


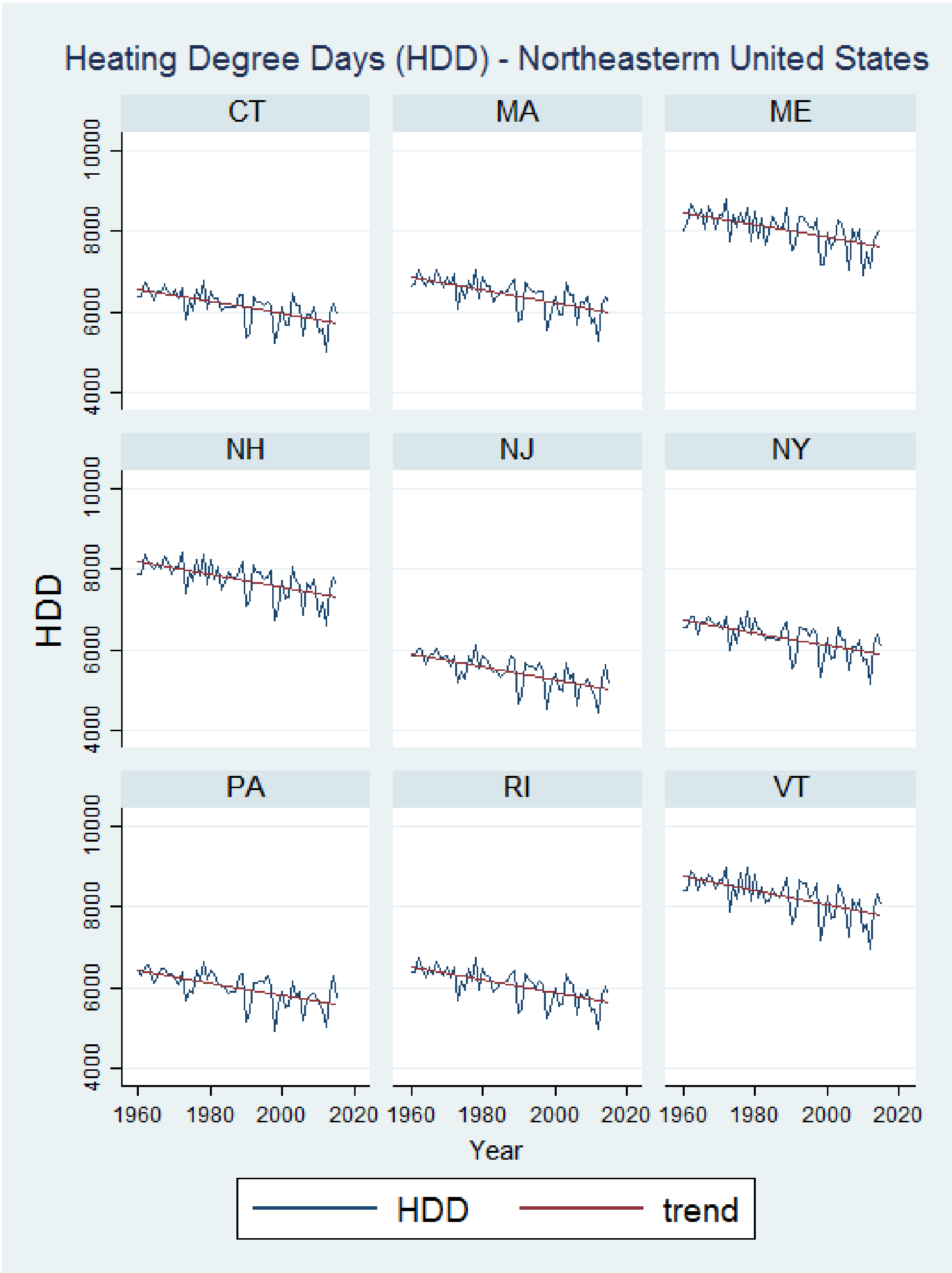
Figure 15: Cooling Degree Days in the Northeastern United States




Source: National Oceanic and Atmospheric Administration (NOAA).

Note: Abbreviations used in the graph: Connecticut (CT) - Massachusetts (MA) - Maine (ME) –New Hampshire (NH) – New Jersey (NJ) – New York (NY)- Rhode Island (RI) – Pennsylvania (PA) - Vermont (VT)

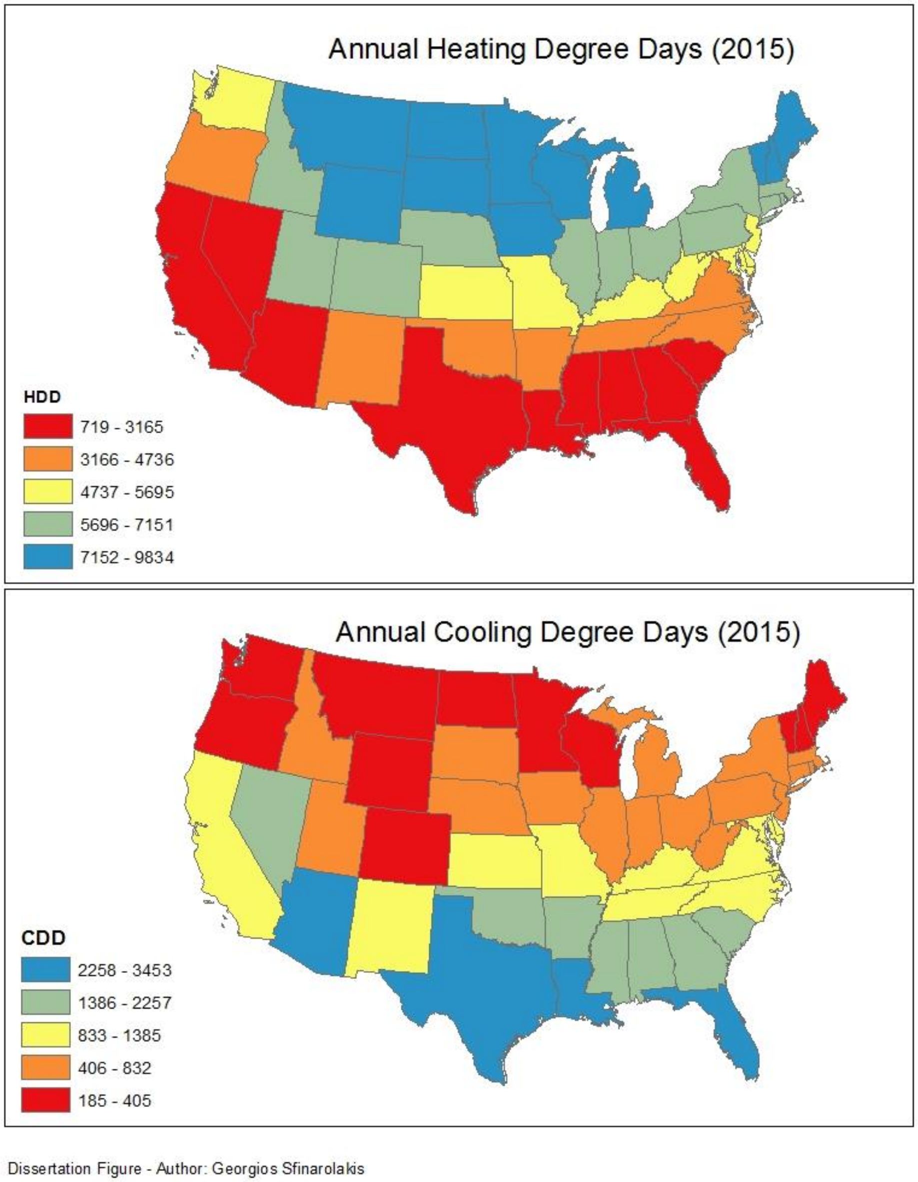
Figure 16: Heating Degree Days in the Northeastern United States




Source: National Oceanic and Atmospheric Administration (NOAA).

Note: Abbreviations used in the graph: Connecticut (CT) - Massachusetts (MA) - Maine (ME) –New Hampshire (NH) – New Jersey (NJ) – New York (NY) - Rhode Island (RI) – Pennsylvania (PA) - Vermont (VT)

Figure 17: Degree Days – US Map (2015)




Source: National Oceanic and Atmospheric Administration (NOAA).

Figure 18: New England Map

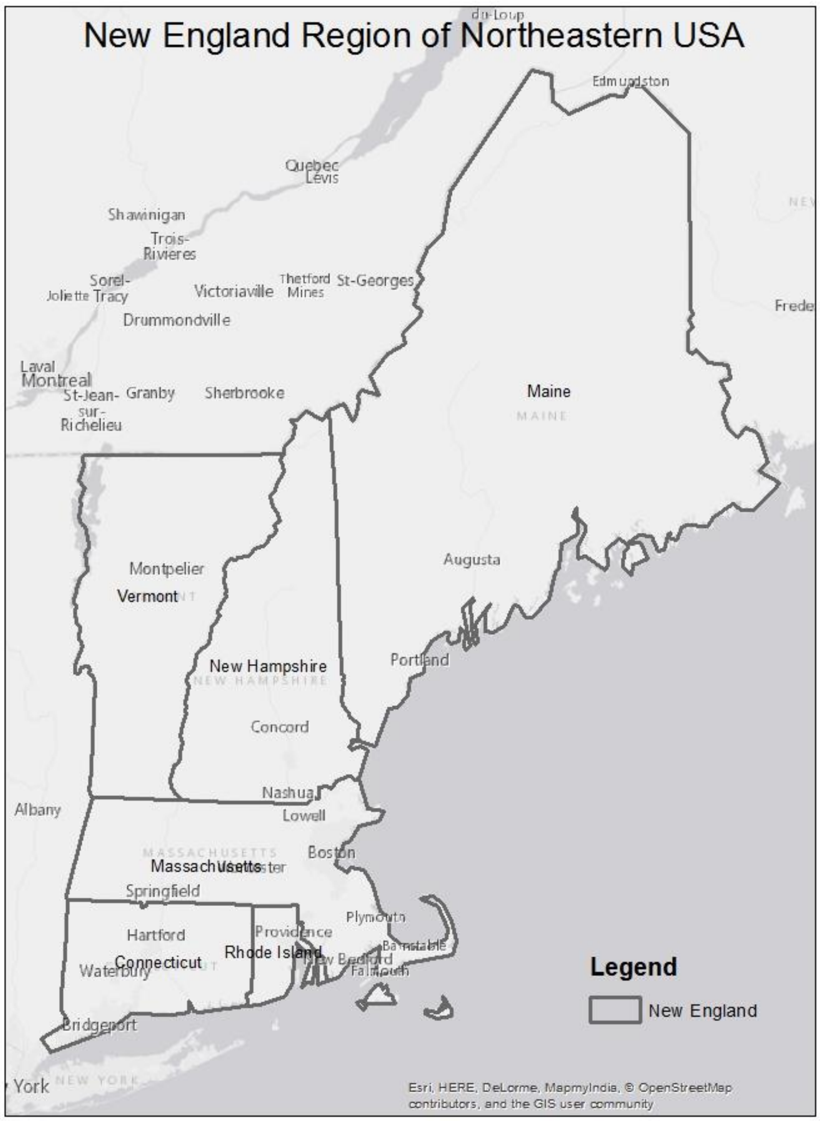
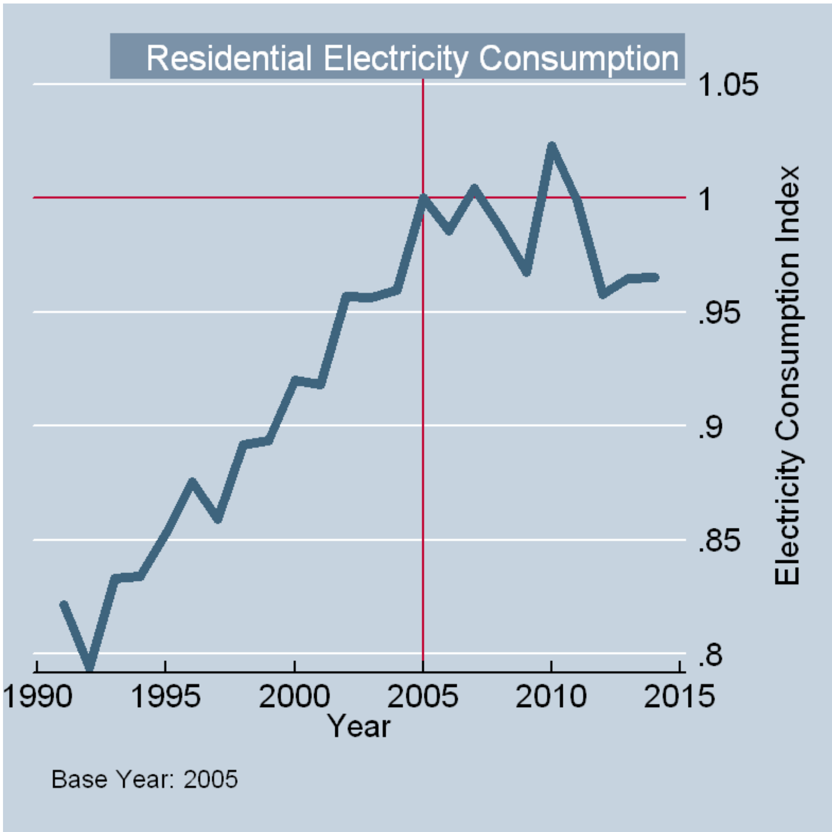


Figure 19: Residential Electricity Consumption Index in US




Note: Index for the Residential Electricity Consumption was produced by normalizing annual consumption to the consumption of base year 2005.

Source: Author by utilizing time series data reported by the EIA

Table 21: Energy Efficiency Variables Reported by Year (EIA-861)

| | | 2005 | 20066 | 20077 | 2008 | 2009 | 20100 | 20111 | 20122 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Utility id | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| | Utility name | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| (1) | EE Incremental | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| | EE Incremental | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| | EE Incremental | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| | EE Incremental | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| | EE Incremental | (*) | (*) | (*) | (*) | (*) | yes | yes | yes | yes | yes | yes |
| (2) | EE Annual Res | yes | yes | yes | yes | yes | yes | yes | yes | no | no | no |
| | EE Annual Com | yes | yes | yes | yes | yes | yes | yes | yes | no | no | no |
| | EE Annual Ind | yes | yes | yes | yes | yes | yes | yes | yes | no | no | no |
| | EE Annual Tran | yes | yes | yes | yes | yes | yes | yes | yes | no | no | no |
| | EE Annual Total | (*) | (*) | (*) | (*) | (*) | yes | yes | yes | no | no | no |
| (3) | EE_lc_res | - | - | - | - | - | - | - | - | yes | yes | yes |
| | EE_lc_com | - | - | - | - | - | - | - | - | yes | yes | yes |
| | EE_lc_ind | - | - | - | - | - | - | - | - | yes | yes | yes |
| | EE_lc_tran | - | - | - | - | - | - | - | - | yes | yes | yes |
| | EE_lc_tot | - | - | - | - | - | - | - | - | yes | yes | yes |
| (4) | DirectCostEE_Res | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | DirectCostEE_Com | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | DirectCostEE_Ind | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | DirectCostEE_Tran | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | DirectCostEE | yes | yes | yes | yes | yes | yes | yes | yes | yes* | yes* | yes* |
| (5) | IncentiveEE_Res | - | - | - | - | - | yes | yes | yes | yes | yes | yes |
| | IncentiveEE_Com | - | - | - | - | - | yes | yes | yes | yes | yes | yes |
| | IncentiveEE_Ind | - | - | - | - | - | yes | yes | yes | yes | yes | yes |
| | IncentiveEE_Tran | - | - | - | - | - | yes | yes | yes | yes | yes | yes |
| | IncentiveEE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| (6) | DirectCost_lmres | - | - | - | - | - | yes | yes | yes | no | no | no |
| | DirectCostl_mcom | - | - | - | - | - | yes | yes | yes | no | no | no |
| | DirectCost_lmind | - | - | - | - | - | yes | yes | yes | no | no | no |
| | DirectCost_lmtran | - | - | - | - | - | yes | yes | yes | no | no | no |
| | DirectCost_lm | yes | yes | yes | yes | yes | yes | yes | yes | no | no | no |
| (7) | Incentive_lmres | - | - | - | - | - | yes | yes | yes | no | no | no |
| | Incentive_lmcom | - | - | - | - | - | yes | Yes | yes | no | no | no |
| | Incentive_lmind | - | - | - | - | - | yes | yes | yes | no | no | no |
| | Incentive_lmtran | - | - | - | - | - | yes | yes | yes | no | no | no |
| | Incentive_lm | yes | yes | yes | yes | yes | yes | yes | yes | no | no | no |
| (8) | IndirectCost_Res | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | IndirectCost_Com | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | IndirectCost_Ind | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | IndirectCost_Tran | - | - | - | - | - | yes | yes | yes | yes* | yes* | yes* |
| | IndirectCost | yes | yes | yes | yes | yes | yes | yes | yes | yes* | yes* | yes* |
| | TotalCost_Res | - | - | - | - | - | yes | yes | yes | yes** | yes** | yes** |
| | TotalCost_Com | - | - | - | - | - | yes | yes | yes | yes** | yes** | yes** |
| | TotalCost_Ind | - | - | - | - | - | yes | yes | yes | yes** | yes** | yes** |
| | TotalCost_Tran | - | - | - | - | - | yes | yes | yes | yes** | yes** | yes** |
| | TotalCost | yes | yes | yes | yes | yes | yes | yes | yes | yes** | yes** | yes** |

**Notes**

(1) Efficiency Incremental Effect for residential, commercial, industrial and transportation

(2) Energy Efficiency Annual Effect for residential, commercial, industrial, transportation

(3) Life cycle efficiency savings (4) Direct efficiency cost by sector (5) Incentives efficiency

(6) Direct cost load management (7) Incentives load management (8) Indirect cost by sector

(*) yes: Direct and indirect efficiency cost are reported together as 'other'.

(**) yes: Total Cost was estimated as the sum of incentives and 'other' costs

Table 22: Building Efficiency Revenue in US (million $)

| Segment | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|
| Design Services | $3,128 | $3,351 | $3,850 | $4,336 |
| Building Envelope | $9,645 | $11,919 | $12,766 | $14,127 |
| HVAC | $11,532 | $12,306 | $13,184 | $14,140 |
| District Energy and CHP | $925 | $1,189 | $850 | $925 |
| Water Heating | $1,197 | $1,357 | $1,490 | $1,639 |
| Lighting | $9,992 | $10,701 | $22,024 | $24,666 |
| Appliances and Electronic Equipment | $148 | $208 | $227 | $472 |
| Demand Response & Enabling IT | $2,748 | $2,748 | $3,356 | $3,431 |
| Total | $39,315 | $43,779 | $57,747 | $63,736 |

*Note:* Data captured from Advanced Energy Economy Market Report, prepared by Navigant Research

Figure 20: Residential Cost of Electricity - Northeast US

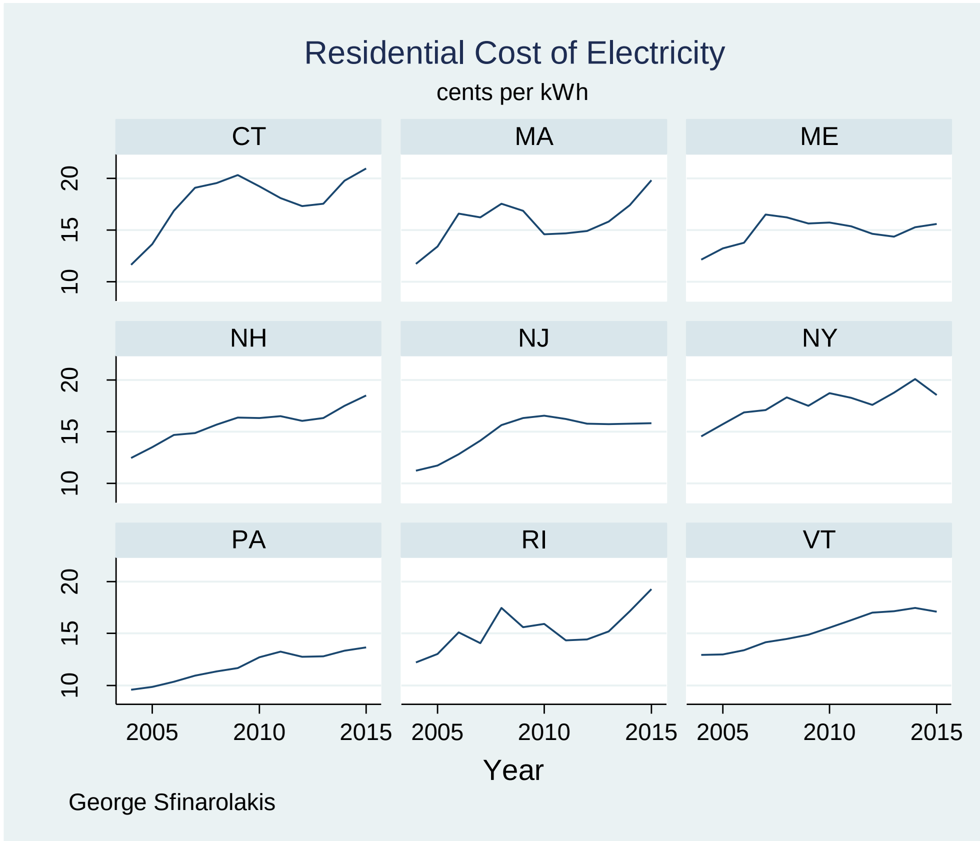


Table 23: Variable Description – Covariates at DiD and SCM

ESRCD: Electricity price in the residential sector - Dollars per million Btu

GDPRX: Real gross domestic product. - Million chained (2009) dollars

TEGDS: Energy expenditures as percent of current-dollar GDP - Percent

TPOPP: Resident population including Armed Forces. - Thousand

WYTCB: Wind energy, total consumed. - Billion Btu

WYTXB: Wind energy, total end-use consumption. - Billion Btu

CDD: Cooling degree days

HDD: Heating degree days

PRC_1unit: Percentage of housing structures with one unit

PRC_20unit: Percentage of housing structures with 20 or more units

PRC_1bdrm: Percentage of housing with one bedroom

PRC_elche: Percentage of housing with electrical heating

PRC_occup: Percentage of Occupied housing units

Table 24: Incremental electricity savings by state in Northeastern U.S. (2015)

| State | Incremental savings (MWh) | % of 2015 retail sales |
|---|---|---|
| Rhode Island | 222,822 | 2.91 |
| Massachusetts | 1,472,536 | 2.74 |
| Vermont | 110,642 | 2.01 |
| Maine | 183,347 | 1.53 |
| Connecticut | 435,740 | 1.48 |
| New York | 1,559,665 | 1.05 |
| Pennsylvania | 904,238 | 0.64 |
| New Hampshire | 64,869 | 0.59 |
| New Jersey | 409,957 | 0.55 |

*Source:* AEEE The 2016 State Energy Efficiency Scorecard

Table 25: Proved Reserves of Fossil Fuels

| Year | Crude Oil Billion (bbl) | Natural Gas (Tcf) |
|---|---|---|
| 1980 | 641.85 | 2,585.68 |
| 1985 | 701.49 | 3,401.25 |
| 1990 | 1,002.27 | 3,980.89 |
| 1995 | 1,000.62 | 4,981.45 |
| 2000 | 1,018.18 | 5,149.96 |
| 2005 | 1,278.45 | 6,044.93 |
| 2010 | 1,356.69 | 6,638.19 |
| 2015 | 1,657.95 | 6,950.51 |

*Source*: Author by utilizing time series data reported by the EIA U.S. Energy Information Administration

Table 26: Mean Value Comparison of the Treated and Synthetic control output

RI Mean Annual Residential Electricity Consumption in MWh

| Year | $Y_{RI}$ Treated | $Y_{RI}$ Synthetic |
|---|---|---|
| 2005 | 7.4388719 | 7.428182 |
| 2006 | 7.0356641 | 7.0929316 |
| 2007 | 7.2916083 | 7.2541209 |
| 2008 | 7.0735087 | 7.1193668 |
| 2009 | 6.7963095 | 7.0001828 |
| 2010 | 7.2402263 | 7.3370818 |
| 2011 | 7.2368846 | 7.3503314 |
| 2012 | 7.1681738 | 7.2487761 |
| 2013 | 7.2220592 | 7.2473378 |
| 2014 | 6.9958849 | 7.1093024 |
| 2015 | 7.1230578 | 7.2184379 |

Table 27: State Weights in the synthetic Rhode Island

| State | Weight |
|---|---|
| CT | 0 |
| MA | 0 |
| NH | 0 |
| NJ | 0.003 |
| NY | 0.252 |
| PA | 0.04 |
| VT | 0.705 |

Table 28: Residential electricity consumption predictor means before the LCP

| Predictor | Treated | Synthetic |
|---|---|---|
| ln_price_elect | 3.71726 | 3.71833 |
| ln_income | 3.86127 | 3.82305 |
| ln_cdd | 6.39757 | 5.83689 |
| ln_hdd | 8.65696 | 8.8787 |
| prc_1unit | 0.55071 | 0.59924 |
| prc_20unt | 0.06901 | 0.08007 |
| prc_1bdrm | 0.14501 | 0.13634 |
| prc_elche | 0.07069 | 0.05159 |
| prc_occup | 0.00208 | 0.00387 |
| ln_kwh_consumer(2007) | 1.98672 | 1.98205 |
| ln_kwh_consumer(2006) | 1.95099 | 1.96243 |
| ln_kwh_consumer(2005) | 2.00672 | 2.00728 |

Root Mean Squared Prediction Error (RMSPE) -> .0071665

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